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Enhancing Financial Stability by Implementing Incentive-Based Risk Control Mechanisms

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a. o. Univ.-Prof. Dr. Wolfgang Aussenegg
E330 – Institut für Managementwissenschaften
Technische Universität Wien

o. Univ.-Prof. Dr. Stefan Bogner
Department Chair – Department of Finance, Accounting and Statistics
Director of Institute for Finance, Banking and Insurance
Director of Research Institute for Regulatory Economics
Wirtschaftsuniversität Wien

eingereicht an der Technischen Universität Wien
Fakultät für Mathematik und Geoinformation

von

Dipl.-Ing. Mag. Bernhard Kronfellner
The Boston Consulting Group
Matrikelnummer: 0152843
Schottenfeldgasse 66/34
A-1070 Wien

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To my parents

Abstract

Problem: Over the last decades the role of finance in economies has increased radically: trading volumes climbed up, quantitative innovations have made services and products more complex, and many industries and even states became highly leveraged especially financed by financial institutions. Before the financial crisis of 2007-2009 this growth was considered to enhance both the efficiency and stability. However, the crisis has proven that this hypothesis is not true. The current financial system and regulatory regime could not prevent financial institutions to take, mostly knowingly, tremendous amounts of risk that in case of a down-turn amplify instead of smoothen economic troubles. These risks can lead to a need of massive restructuring of assets and activities within organizations, defaults of institutions or even a cascade of bankruptcies due to contagion. *Objective*: This doctoral dissertation is dedicated to improve stability of financial institutions and the financial system in times of crisis. On a micro- and macroeconomic level, I focus on three dimensions: (i) to reduce the domino-effect (i.e. systemic risk) in cases of local bank defaults or industry-wide shocks (macroeconomic level), (ii) to set incentives to smoothen the risk appetite of banks lately emerged due to public bail-outs (micro- and macroeconomic level), and (iii) to restructure portfolios and organizations (microeconomic level). *Method*: At all levels I apply financial mathematical methods (especially stochastic models of option- and credit-default-pricing) to model relationships in an organization and between organizations. *Results*: The bird´s eye view of the financial system as a whole brought me to the macroeconomic idea to redesign the bank tax (penalize high interlinkages between banks and use the return as tax calculation base) and to introduce an early self-financed bail-out of troubled institutions, in order to lower the costs and need for expensive bank bail-outs. Considering the combination of the macro- and microeconomic view, I describe a mechanism that decreases the risk-taking incentives for managers while enhancing the expected profit and lowering the cash-flow volatility of financial institutions. On a microeconomic level, this dissertation suggests an optimal liquidation strategy for assets and corporate activities with respect to the costs of organizational restructuring.

Zusammenfassung

Problem: Innerhalb der letzten Jahrzehnte hat sich die Rolle der Finanzmärkte in der Wirtschaft stark verändert: Handelsvolumen sind gestiegen, finanztechnische Entwicklungen haben Produkte und Services komplexer gemacht und viele Unternehmen aber auch Staaten haben ihre Fremdkapitalquote dramatisch erhöht. Vor der Finanzwirtschaftskrise herrschte die Überzeugung, dass dieser starke Anstieg im Bankgeschäft zur wirtschaftlichen Effizienz und Stabilität beiträgt. Die Finanzwirtschaftskrise hat jedoch schmerzhaft vor Augen geführt, dass es sich hierbei um ein Pulverfass handelt, welches leicht finanztechnische oder wirtschaftliche Probleme verstärkt anstatt diese abzufedern. Das Geschäft mit Risiken ist nicht nur in der Risikomessung sondern vor allem auch bei den Incentivierungsmechanismen der Gesamtbank- und Finanzmarktsteuerung verbesserungswürdig. *Ziel:* Im Rahmen dieser wissenschaftlichen Arbeit werden einerseits die "pre-crisis"-Mechanismen analysiert und finanzmathematische Modelle für diverse Verbesserungsvorschläge in der "post-crisis"-Zeit auf das Potential eines stabilisierenden Effektes auf die gesamte Finanzwirtschaft erstellt. Fokus der Arbeit liegt (i) auf einer im Sinne der Finanzmarktstabilität sinnvollen Verwendung der Bankensteuer (makroökonomische Ebene), (ii) auf dem Desgin eines Incentivierungs-Mechanismus um den Risiko-Appetit von Banken zu minimieren (mikro-/makroökonomische Ebene), und (iii) auf dem risikoadjustierten Abbau von Assets und Mitarbeitern (mikroökonomische Ebene). *Methode:* Die stabilisierenden Effekte dieser Maßnahmen, welche Stabilität, höhere erwartete Ergebnisse und geringere Profit & Loss-Volatilität nicht nur der Banken-Branche sondern der gesamten Realwirtschaft zur Folge haben, werden finanzmathematisch und systemanalytisch mittels Simulation erarbeitet und nachgewiesen. *Ergebnisse:* Auf makroökonomischer Ebene wird ein selbstfinanzierter Bank-Rettungs-Mechanismus erarbeitet, der durch eine Banksteuer finanziert wird, die auf den Erfolg der Banken und ihren Verbindungsgrad basiert. Eine kombinierte Betrachtungsweise der makro- und mikroökonomischen Ebene führt zu einem regulatorischen Mechanismus, der den Risikoappetit von Bank Managern eindämmt. Die mikroökonomische Ebene beschäftigt sich mit einer optimalen Abbaustrategie von Assets, welche neben Kosten auch organisatorische Risiken betrachtet.

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What would life be without an understandingly partner, a supporting family and trusted friends. I could describe myself as one of few blessed people who always gets support and backup from all of them. Nevertheless, nobody has been more important to me than my parents. Ever since they gave me the unconditional support in my life´s journey and made my development and success possible.

To all of you, I owe you a lot and I hope to get opportunity to accomplish.

Bernhard Kronfellner

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1 Introduction

The economy does not increase constantly, but is exposed to cycles. To understand, forecast, and even attempt to alter expansion, recession, and depression are the main concerns of mathematical economic research. This dissertation does not focus on the causes of crisis, but of how to deal with it.

The study of the recent financial crisis 2007-2009 and the current public debt crisis show the financial system quite plainly how local problems (e.g. in the mortgage market) can spill over to the whole financial world and can even infect the real economy. Due to significant interlinkages between companies, many companies and states were driven into or close to bankruptcy. Even though financial engineering over the last decades have suggested how to measure the inherited financial and business risk more accurate, the financial industry and, as a consequent, the real economy are currently struggling from enormous risks in their balance sheets. The current regulatory regime and innovations in risk management could not prevent financial institutions to take tremendous amounts of risk. Recent regulatory developments (such as the Basel III Accord, the implementation of bank taxes in certain countries, application of new accounting standards, etc.) have certainly amended the situation but the incentives for bankers to take riskier business decision still remain. This higher risk appetite in banking is especially based on the compensation schemes and on the fact that large institutions can expect a public bail-out in case of default. Due to creative accounting, management will (again) find ways to circumnavigate rules to fulfil their risk appetite. Thus, beside setting new capital requirements or limiting leverage ratios, an appropriate question for regulators should be to provide incentive such that institutions enhance indirectly the industry-wide stability by directly striving to boost their profits. Besides a deeper understanding of the causes of this financial turmoil, in this dissertation I will also consider the question of how to deal with crisis. In particular, I will elaborate a model for companies to restructure assets and business activities in times of crisis.

1.1 Paradigm Change in Finance

In the scientific world, theories and thereof derived paradigms are used to explain phenomena and empirical observations. In particular, drastic economic fluctuations, such as crises, can often not be described by the current recognized set of theories. Over the last century of economic research, it has been shown that the evaluation of the empirical irregularities very often leads to a new theory and a change of paradigm. E.g. the Great Depression completely changes the study of economic cycles.[1] In order to deal with the inadequacies of the depression and the existing economic theory (the classical model dating back to the founding father of economics, Adam Smith, who was refined by economist such as David Riccardo, Jean-Baptiste Say, and John Stuart Mill), the only way to describe the events of the 1930ies was to change the existing theory to the Keynesian Theory (dating back to John Maynard Keynes) and later to the Monetarist Model (especially embossed by Milton Friedman).[2] In same manner as crises can influence the economic paradigm, groundbreaking innovations (such as the development of railways and steel production in the middle of the 19^{th} century) can launch new economic theories.[3]

The same holds true for the paradigm changes in finance; either crises that are not explicable with existing theories or innovations lead to a rethinking of approaches in use. The course of paradigm changes in finance can be described as follows: [4]

The first paradigm, *The Old Finance*, dates back to the merchants of Venice[5] and describes basic concepts of how to trade, to take commissions, and to invest in promising projects. Based on this knowledge used in practice for centuries, Joel Dean (1951), scientifically developed corporate finance concepts such as the consideration of discounted cash flow and the internal rate of return. Additionally, the Old Finance focuses on approaches based on balance sheet and profit-/loss-statement ratios, e.g. Return on Equity (ROE), Return on Investment (ROI), Earning Before Interest and Taxes (EBIT), Economic Value Added (EVA), …

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1 *See* Eilenberger et al. (2008).
2 *See* Knoop (2004).
3 *See* Schumpeter (1939).
4 *See* Eilenberger et al. (2008).
5 The behaviour and mind-set of these ´ancient businessmen´ was perfectly characterised in the play ´Merchant of Venice´ by William Shakespeare in 1600. (Compare Eilenberger et al. (2008)).

The innovation of the worldwide financial market and the need for a deeper understanding of its fluctuations lead to a new set of financial theories, subsumed as the paradigm *The Neoclassical Finance*.[6] The nobleprice-winners, Modigliani and Miller (1958), describe the efficiency of financial markets. They consider the movements on the markets as Random Walk. Furthermore, they regard the price of any security on the market as fair and that it reflects all actions of a company. In the same spirit, the monetarist, Irving Fisher (1930), build the theoretical fundament of the split of principals (shareholders) and agents (managers). He could show in his separation theorem[7] that the corporation´s objective of profit maximization can be separated from the preferences of its shareholders.

Under the assumptions of efficient financial markets, Markowitz put forward the *Modern Portfolio Theory (MPT)*[8] in which he considers ´… expected return a desirable thing and variance of return an undesirable thing …´ and plots the relation between return and variance of return. Based on the Modern Portfolio Theory, Sharpe (1964), Lintner (1965), and Moissin (1966), independently developed the *Capital Asset Pricing Model (CAPM)*, that describes the appropriate return of an already well-diversified portfolio according to the MPT. According to the belief of randomly fluctuating financial markets and of efficient markets, i.e. that all existing information is already considered in the current asset price, Malkiel (1973) published his bestseller book in Finance, *´A Random Walk Down Wall Street´*. Likewise, the start of *Option Pricing Model*, published by Black and Scholes (1973), who, firstly, could calculate the price of put and call options, but only if ´…options are correctly priced in the market…´.

In the 1980ies and 1990ies, again, an innovation revolutionized the financial research. Computers emerged and could evaluate huge amounts of financial data. In accordance with the Austrian philosopher, Sir Karl Popper, who characterised a valid theory by its falsifiability[9], an armada of researchers all over the world tried to verify or falsify financial theories by using historical data. This new area of *Empirical Finance* has shown, that the markets are not as efficient and random as expected in the previous paradigm. In particular, Lo and MacKinley (1999) outlined irregularities and even some possibilities of forecasting in their book *´A Non-Random Walk Down Wall Street´*. Applying new statistical software and

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6 *See* Eilenberger et al. (2008).
7 *See* Fisher (1930).
8 *See* Markowitz (1952).
9 *See* Popper (1934).

estimation methods allowed the nobleprice-winner of 2003, Engel (1982), to describe ´volatility clustering´ in financial time series with ARCH-Models[10]. Furthermore, Fama and French (1992) overwhelmed the CAPM by showing that not only Beta[11] influences significantly the return of financial time series but also (at least) two other indicators[12]. Accordingly, many researchers incorporated more indicators to (statistically significant) describe stock returns and other asset classes. This field of research is named *Arbitrage Pricing Theory (APT)*.

However, crises, such as the Dot.Com-downturn in 2001, reveal that the empirical-´looking-back´- approach could not explain or forecast all fluctuations. Two new paradigms emerged widening existing mathematical theories: First, *Behavioural Finance* incorporates market rumours and psychological explanations of market movements due to fear. Second, *Corporate Finance* focuses more on financial structure and assets of corporations than on historical data of its stock price or rumours and beliefs. It also involves the Principal-Agent-Theory, i.e. the problem of asymmetric information and moral hazard if a principal hires an agent to run its company.

An extension of this field of research is *Strategic Corporate Finance*, which is brought up by Eilenberg, Haghani, Kötzle, Reding, and Spremann (2008). This approach reveals the positive forecasting value of strategic management decisions on future stock fluctuations. These strategic management decisions contain e.g. planed restructuring and expansion, mergers and acquisitions, communication strategies, financial distress, knowledge transfers of investors, etc.

Both, the financial and public debt crisis show how the financial world could influence the stability of the whole economy and even states. This imposes that the efficient market hypothesis that more financial activities (growth of trading volume, increase of complex products and services, possibility to trade risk, etc.) is axiomatically beneficial for the social welfare must be rejected[13]. Considering the fact that either innovations or deep crises change

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[10] Autoregressive Conditional Heteroskedasticity.

[11] Parameter of asset fluctuation that can be explained by the movements of the market return (minus the risk free interest rate).

[12] In the Three-Factor Model of Fama and French the two other indicators are the market capitalization (calculated as small minus big (SMB) market capitalization) and book-to-market-ratio (calculated as high minus low (HML) book-to-market-ratio).

[13] *See* Turner (2010).

the course of paradigm, it now can be expected that this ´double dip crisis´ will alter the relation between financial markets and governments. Regulators and governments strive to elaborate new rules to reduce the risk steming from the financial world. Thus, this need evokes the research question of how to build mechanisms that strengthen the financial system and, consequently, make economies more resilient. The objective is to design a stabilizing regulatory framework such that market participants indirectly increase the overall system stability only by directly focusing on its own profit. Instead of setting new limitations, regulatory incentives should reward organizations to act in means of the social welfare. This dissertation contributes three different models on a macro-, marco-/micro-, and microeconomic level to this new field of research that might leads to a new paradigm in finance.

1.2 Critical Assessment of the Regulatory Regime

Proposing new risk models and regulatory instruments without any assessment of the current situation might be improperly. In this section, I give a quick overview of the instruments in use and of the recently in the academic literature evoked main critics of the current regulatory system.

1.2.1 Current Regulatory Instrument and the Advantage of a Change to an Incentive-Based Control System

The economic stability of a country depends (among other parameters) on the soundness of its financial industry. Thus, every country with a well-developed banking system imposes rules to its banks that they have to obey to be part of the banking system. The history of governmental bank regulation dates back to the time after the Great Depression where the financial world experienced a bank panic and a collapse of the whole system.[14] Many regulatory instruments, such as the deposit insurance, were established in these days. Nevertheless, the industry has experienced tremendous changes over the time. As a consequence of the financial crisis and the experience that these partly outdated mechanisms failed to prevent the development of the current crisis, the academic and regulatory world

[14] *See* Eilenberger et al. (2008).

assess these instruments and its ability to (a) restore (ex-post) and (b) retain (ex-ante) financial stability.

According to Freixas and Rochet (2008), regulatory instruments can be classified in six different types:

- Deposit interest rate ceilings
- Entry, branching, network, and merger restrictions
- Portfolio restrictions, including reserve requirements
- Deposit insurance
- Capital requirements
- Regulatory monitoring and supervision (including closure policy)

All these mentioned schemes are designed, installed, and monitored by the government. Thus, all these measures are seen as a burden by financial institutions.

1.2.2 Critics on the Lacking Regulatory Regime

Among many critics, this sub-section tries to select the main arguments. In addition, the following remarks can also be seen as a check-list of aspects and problems new mechanisms can and have to solve.

(a) Focus on reserve- and capital-requirements and leverage ratios is not enough to prevent bankruptcies and to anticipate systemic risk

In analysing current[15] and upcoming[16] regulatory regimes, the common way of how to control expansions and restructurings of banks is to set boundaries; such as the minimum capital requirement or the recently implemented maximum leverage ratio. However, the case of Northern Rock[17] has proven that using mainly capital requirements to regulate banks is not enough. Due to a lack of liquidity, the British authority had to bail-out the bank for GBP 23 billion even though the regulatory capital (calculated according to Basel II) was only GBP 1.5 billion[18]. In between these (more or less) fixed boundaries, public authorities have no instrument that can – if needed in the specific economic situation – smoothen the pro-

[15] E.g. Basel II
[16] E.g. Basel III
[17] *See* Atkinson and Blundell-Wignall (2009).
[18] *See* Dewatripoint et al. (2010).

cyclical business cycles of banks[19]. Thus, banks can henceforth continue to grow or shrink as fast as they want, which increases the P&L-volatility and, hence, the default risk of the bank.

Besides the observation, that reserve- and capital-requirements as well as leverage ratio limitations can not prevent financial institutions from bankruptcy, the current (Basel-) regime is also unable to anticipate systemic risk. Dewatripont et al. (2010) mention several resons: (i) many institutions, that got into troubles during the crisis, were reasonably capitalized, but were exposed to a lack of liquidity; (ii) risk models are parameterized due to normal times and the looking back approach does not consider extreme events; and (iii) current regimes (especially the Basel-Accords) only focus on individual banks and not on the financial system as a whole.

(b) No instrument addresses the risk of intensive growth and restructuring

Even though the financial market is rigorously regulated and controlled by public authorities, banks experience higher growth rates and steeper recessions than other industries. Rajan (2005) explains this higher risk taking by a change in the incentive structure of investment managers. In the 1950s and 1960s bank managers where paid largely a fixed salary[20]. Nowadays, however, the salaries highly depend on the returns. According to Rajan, the problem behind this compensation structure is that there is a mismatch between negative and positive returns. The bonus is mostly related to a positive than to a negative bank performance. Therefore, bank managers have a higher incentive to take risks as they do not have to care about the downside.[21]

Dewatripont and Rochet distinguish between ex-ante and ex-post crisis management.[22] This financial crisis has already developed mechanisms to rescue the financial intuitions individually, which can be seen as a first attempt to establish a mechanism to deal with distressed banks (ex-post mechanism). Evidently, the new capital requirements according to the Basel III regime is trying to prevent banks to become insolvent (ex-ante mechanism), but this accord is definitely too inflexible to quickly react to harmful developments in the financial markets or to punish banks that are increasing their risk too quickly. In this regard,

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[19] Even though Basel III has planed to establish countercyclical buffer in times of excessive credit growth of 0% – 2.5% of RWA, regulators have not implemented any other mechanism to directly control expansions or restructurings of institutions.

[20] *See* Rajan (2005).

[21] In chapter 3, I will argue that this situation is similar as if bank managers are holding a call option on the return.

[22] *See* Dewatripont, Rochet, Tirole (2010).

Dewatripont, Rochet, and Tirole (2010) point out that ´… a single capital requirement … is not enough to limit risk taking by banks.´[23]

This higher risk appetite can easily be shown by considering the one year moving average volatility of the S&P 500 Index (SPY), representing all industries, and the moving average volatility of the S&P Banking Index (BIX)[24]. The average volatility over the last 5 years of the S&P 500 Index is 25% whereas the S&P Banking Index shows 53% average volatility.[25] Using stock prices as indicators for corporate risk taking, Figure 1.1 illustrates that bank companies tend to choose a (significantly) more volatile business model than other companies.

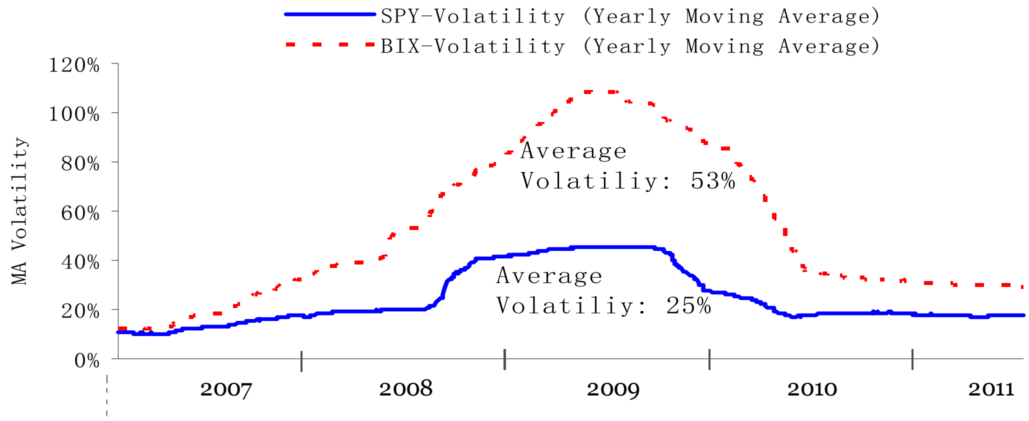

Figure 1.1: Comparison of the volatility of the S&P 500 (SPY) and the S&P Banking Index (BIX)

This Figure shows a comparison of the one year moving average of the volatility (standard deviation) of the S&P 500 Index (SPY) and the S&P Banking Index (BIX) over the last 5 years, i.e., from the 3rd of May 2006 until 29th of April 2011. The graph starts in the second quarter of 2007 as the calculation of the yearly moving average causes a time lag of one year.

Both a tremendous growing and shrinking of banks can cause harm to the economy. On the one hand, a staggering growth, mostly steming from trading, increases the P&L-volatility and, consequently, the riskiness (default risk) of the institution. On the other hand, a too fast shrinking organisation, that runs a restructuring plan without any focus on the organisational stability, increases the organizational risk. This risk includes especially the loss of know-how

[23] *See* Dewatripont, Rochet, Tirole (2010).

[24] The S&P Banking Index (BIX) is a subindex of the S&P 500 and contains 16 mid- and large-cap financial institutions. The BIX is the commonly used index to model the developments of financial institutions.

[25] Even without the volatility boost during the financial crisis, the average volatility of the BIX is significantly higher than the volatility of the SPY.

and the destruction of well-functioning and sometimes not documented organisational processes (see chapter 4). A close look at the Profit & Loss (P&L) of banks before and within the crisis illustrates where the volatile growth rates come from: especially the trading income[26] causes volatile P&L-statement. Both changes in asset holding and asset prices[27] are source for the fluctuations. This shows that the P&L-volatility is not an external factor, but a decision of the bank towards risk.

In short, both scenarios, a too fast growing and a too fast shrinking organisation, can harm the organization and, consequently, the economy. Iceland is an extreme case of how a crashing banking system can bring down the whole economy. Therefore, public authorities need to find ways[28] to penalize organisations that are changing to fast.

(c) The current monetary policy is a too blunt instrument to prevent future financial crisis

In the recent economic literature, the low interest rates over the past 10 years are often cited as one of the causes for the financial crises[29]. In particular, from 2002-2005, the low interest rates (besides the risk transmission from the issue to an external risk-taker by securitization and thus the excessive lending to private sector[30]) in the US has been nourishing the crisis[31]. Both the cheap liquidity cost and a lax risk assessment in the lending process pushed up housing and asset prices and directly led into bubbles.

In order to prevent crises, one can not only critize the timing of the US Federal Fund Rates alteration, but also the instrument itself. As Bruni (2009) pointed out, monetary policy in the means of altering interest rates plays an important role in the long-term organisation of financial markets and the economy. Especially a counter-cyclical monetary policy can moderate booms and, hence, diminishes the risk of bursting bubbles. However, the classical monetary policies are unable to regulate the market in emergency situations. Both the

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26 Besides the trading income, a bank earns money from two other sources: from interest rate differences (interest income), from fees and commissions for their services (commission and fee income).

27 Asset pricing depends on the type of classification according to IFRS-Standards: Fair-Value , Held-to-Maturity, Loan & Receivables, Available-for-Sale.

28 Rajan (2005) points out in his paper ´Has Financial Developments Made the World Riskier?´ that authorities are not able to penalize managers who take to much risk.

29 *See* Stiglitz (2010).

30 *See* Hellwig (2009).

31 *See* Bruni (2009).

European Central Bank[32] and the Federal Reserve Bank describe the interest rates as a ´too blunt instrument´ to regulate the fast moving financial markets. The mid- and long-term side-effects of interest rate alteration are vast and often cannot be foreseen[33]. As a consequence of these recent understandings, regulators and academics are striving to find a new monetary policy mechanism that can help to avoid bubbles[34], enhance financial stability, and only has an influence on the financial market; completely uncoupled from wide-economic side-effects.

(d) Treatment of distressed financial institutions has to be harmonized

It is known for decades that large, i.e., ´too-big-to-fail´, financial institutions are system-relevant for financing an economy and, consequently, regulators and governments always strive to bail-out large insolvent banks. However, this key element of regulators ´… has so far attracted little attention …´[35] and is needed to be harmonized in order to fend the pressure of lobbies and politicians. Even in the framework of the EU State Aid Process (see chapter 4), we have seen various kinds of treatment of distressed banks, i.e., every viability report or restructuring plan has been treated differently.

(e) Moral hazard of bank bail-out – an unfair but anticipated advantage for banks

The argument that financial institutions are privately financed companies and, thus, only have to fulfil the wishes of its shareholders (or stakeholders at most) is just not true, even though often used by the banking lobby that wants to diminish regulatory influence. In fact, an economy requires a well-functioning financial system and banks as intermediares that accept deposits and transform these deposits into lending activities in order to finance business activities of the economy. As a consequence public authorities have to regulate the financial sector, since the whole economy relies on the financial industry and, moreover, has to bail-out insolvent banks. These expected and already anticipated bail-outs in case of bankruptcy is one of the main reasons for the excessive risk taking in the banking industry.

The case of Lehmann Brothers in September 2008 has further shown that a strategy of no governmental bail-out is even more costly to the industry and society. Hence, the financial crisis has further underlined this anticipated state aid of too-big-to-fail banks. Beside the certainty of state aid, this situation also gives banks a significant bargaining power to bent

32 *See* EZB Monatsbericht (November 2010).
33 *See* Lahart (2008).
34 *See* Bruni (2009).
35 *See* Dewatripont, Rochet, Tirole (2010).

local regulatory rules. Since the state, as the Lender of Last Resort (LoLR), strives to minimize its state-aid expenses (for the banking industry), it is (sometimes more than it should) willing to find national exceptions to international rules. This fact allows and even further encourages banks to take even more risks.

Furthermore, this ´bankruptcy insurance´ for the banking industry is unfair compared to other industries that do not profit from a respectivce insurance. Consequently, this distortion in competition and the situation of moral hazard need to be equalized by a strict international mechanism with no possibility to national interpretation and adaptation.

1.2.3 Characteristics of a New Mechanism – a Summary

To summarize, in order to prevent or face future financial crisis, regulators need to establish a new mechanisms[36] with the following characteristics:

- focusing on incentive-based risk control in addition to governmental regulation
- penalizing tremendous growth or restructuring, i.e., the high risk appetite by bank managers
- lowering the reliance on capital-requirements, leverage-ratios and interest rate to regulate the financial system
- harmonizing the treatment of sound and non-sound bank
- lowering the inequality and moral hazard emerged by the governmental bank bail-outs

1.3 Research Motivation

Practical experience has shown that not only the accuracy of calculations, but also, or especially, considering systems as a whole can create an impact. Therefore, in this dissertation, I focus on special and important aspects of risks in financial systems and potential new ways to properly regulate these risks. This includes the different incentives of market participants, a variety of risks that are not addressed by regulators so far, and lessons learned from the financial crises.

[36] The necessity of a new mechanism was also postulated by Dewatripont, Rochet, Tirole (2010), even though the characteristics of a feasible new mechanism were not derived as precisely as in this dissertation.

Both the recently emerged discussion of a needed paradigm change after the crisis (see section 1.1) and the necessity for new regulatory mechanisms (see section 1.2) have inspired me to contribute to this research area. However, this dissertation neither is an overview of all reasons of the financial crisis nor gives solutions to all problems emerged. It rather can be seen as a scientific deep-dive of three research questions. On a (i) macro-, (ii) macro-/micro-, and (iii) microeconomic level, I have focused on three practical problems and propose incentive-based models to enhance financial stability:

(i) How to reduce systemic risk in banking? (Macroeconomic level)

It is commonly known, that especially the domino-effect makes defaults or macroeconomic shocks dangerous for both the financial and economic world. However, a mechanism that reduces contagion among financial institutions is still missing and – even though the importance is obvious – only little research in this area has been done so far.

(ii) How to diminish the risk appetite of banks? (Macro-/Microeconomic level)

Regarding the problem of a high risk appetite and moral hazard due to bail-outs in banking, I focus furthermore on manager incentive- and compensation-schemes and try to recalibrate incentive towards smoother business practices.

(iii) How to optionally restructure assets and employees? (Microeconomic level)

At the beginning of the financial crisis of 2007-2009, many financial institutions are dealing with restructuring and liquidation of assets and business segments. Discussions with several bank managements have proven that, besides the concern to execute asset monetarily efficient, bankers are especially worried that financial distress and organizational restructuring might change their organization too quickly, which creates organizational risks. The problem is how to perform planned asset liquidation and, at the same time, organizational restructuring in the best and nevertheless most profitable way.

For all three questions, I strive to elaborate new models such that institutions are monetarily rewarded if they act in the overall economic interest. Thus, by directly optimizing their own P&L they indirectly improve economic stability.

1.4 Key Results and Contributions

The scientific contributions of this dissertation are presented in three chapters where each chapter provides a contribution of its own. These three models are meant for publication in scientific journals and for the submission to academic conferences and are, thus, structured as scientific papers.

Chapter 2 provides a model to reduce the domino-effect of defaults, i.e. the systemic risk in the financial system. Firstly, I focus on the main drivers of this risk. Secondly, upon this understanding and by modelling the financial system with its interactions as stochastic processes, I am able to simulate the two main reasons for systemic risk (macroeconomic shocks and contagion) at the same time and elaborate a concept of how to use most efficiently funds of new bank taxes. The simulation results underline that an early self-finance soft-bail-out and a redesign of bank tax approaches (penalize high interlinkages between banks and use the return as tax calculation base) reduce – compared to current best practice – the probability of default of the financial system, lower the bail-out costs, and decrease the bail-out cost volatility. 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. This chapter forms the basis for the working paper by Aussenegg and Kronfellner (2011). It was accepted for presentation at the following peer-reviewed conferences: The Infiniti Conference on International Finance, 2012, Dublin, The 26th Workshop of the Austrian Working Group on Banking and Finance, 2011, Klagenfurt, The 5th Financial Risks International Forum, 2012, Paris, The Annual Meeting of the European Financial Management Association, 2012, Barcelona, and The Global Financial Conference, 2012, Chicago.

In Chapter 3, I will focus on the problem that the current regulatory regime could not prevent financial institutions to take, mostly knowingly, tremendous amounts of risk. Recent regulatory developments have certainly amended the situation but the incentives for bankers to take riskier business decision still remains. As a lesson learned from the financial crisis of 2007-2009 and to avoid future asset bubbles, new regulatory mechanisms (a bank tax alternative) are needed (i) to smoothen the risk appetite of managers in the financial sector, (ii) to rebalance the lately emerged moral hazard due to public bank bail-outs, and consequently (iii) to enhance the soundness of banks. The used analysis incorporates stochastic models of option- and credit-default-pricing to model creditors´ and managers´ risk taking incentives. The results show that in modelling current performance related remuneration schemes as long call option on the firm profit and bank bail-outs as long put option on the firm value, I construct a new mechanism by using put options issued by the state (where the premium is the new bank tax). This mechanism (i) decreases the risk-taking incentives for managers, (ii) enhances the expected bank profit, (iii) lowers the volatility of financial institutions, (iv) strengthens the soundness of banks, and, thus, (v) reduces the risk of future public bank bail-outs. This chapter forms the basis for the working paper by Aussenegg and Kronfellner (2011). It was accepted for presentation at the following peer-reviewed conference, the Infiniti Conference on International Finance, 2012, Dublin, and The Global Financial Conference, 2012, Chicago.

Chapter 4 considers the organizational risk of restructuring within financial institutions. As a consequence of any crisis (such as the current financial crisis) many organizations have to restructure their activities and assets. This mostly comes along with organizational restructuring as well. Both the asset and the organizational restructuring have an impact on the P&L and the stability of the corresponding company. This chapter derives an optimal liquidation strategy for assets and corporate activities with respect to the costs of organizational restructuring and indicators of organizational stability. Especially, given a fixed amount of assets to be cut down within a fixed timeframe, and considering temporary as well as permanent price impacts and savings due to staff reduction, we obtain the optimal sequence of trades that optimize expected P&L and the stability of the organizational restructuring process over the liquidation period. This chapter forms the basis for the working paper by Aussenegg and Kronfellner (2011). It was accepted for presentation at the following peer-reviewed conference: The 25th Conference of European Chapter on Combinational Optimization, 2012, Antalya.

Finally, chapter 5 concludes and outlines, in brief, the most important findings. Upon the results of the dissertation, I derive suggestions (for instance for regulators, governments, and financial institutions). Clearly, it is not an all-encompassing ´list of things to do´, but only suggestions according to the three considered problems of this dissertation.

2 Soft Bail-Outs Concept to Reduce Contagion in Financial Systems

2.1 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[37]. 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[38], (ii) rising prices of insurance against losses of large financial institutions (i.e. CDS spreads)[39], and (iii) the influence of loss given default (LGD) rates on contagion in the banking system[40].

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

37 *See* Freixas and Rochet (2008).
38 *See* Nicolo and Kwast (2002).
39 *See* Huang et al (2009).
40 *See* Memmel et al (2011).

extent of systemic risk to the on-going trend of consolidation and conglomeration of financial institutions.[41] 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[42] of 1933) by the Gramm-Leach-Bliley Act[43] of 1999 in the US.[44]

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 that temporary grant consolidations[45]. 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[46] towards concentration and conglomeration that increases systemic risk (which can be shown empirically[47]). 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.[48] 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 metaphor, George Soros aims to explain why financial institution conglomeration and consolidation do not lead to a safer financial network.

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41 E.g. Nicolo et al (2003).

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

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

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

45 *See* Broome and Markham (2001).

46 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.

47 *See* Neale et al (2010).

48 Interview of Georg Soros in 2010, published in the documentary ´Inside Job´.

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 chapter 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 modelled in section 2.3. In section 2.4 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 2.5 presents numerical results of the reduction in economic costs and added financial stability. Finally, section 2.6 concludes and derives suggestions for regulators.

2.2 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 behaviour. 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)[49], 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) criticise that the practice of bail-outs of all too-big-to-fail banks generates moral hazard for TBTF-bank towards a higher risk taking.

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

2.3 Modelling 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[50] and system-wide shocks.[51] Fifth, we integrate bank taxation payments in modeling our financial market.

Figure 2.1 aims to deliver an overview of systemic risk and shows the relationship of its relevant parameters, that will be explained in this section.

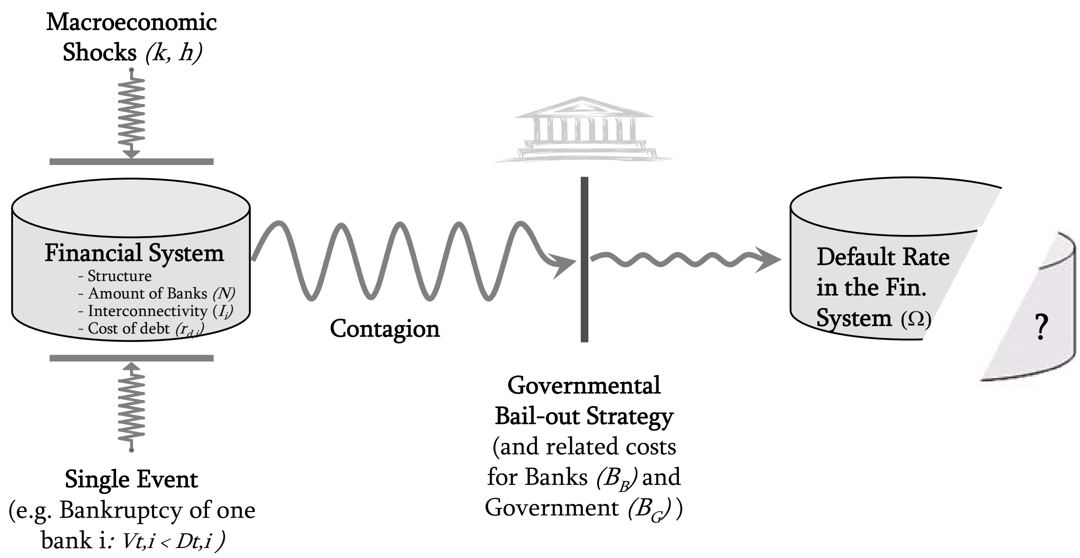

Figure 2.1: Graphical overview of the relevant parameters and divers of the systemic risk

[50] 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).

[51] 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.

2.3.1 Modelling 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[52] (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 $D_t = De^{r_D t}$, 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 modelled as a Geometric Brownian Motion:

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t \tag{2.1}$$

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[53]), the excessive leverage by financial institutions is common practise. This risk taking is widely seen as one reason for the financial crisis.[54] 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

[52] 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.

[53] *See* Diamond and Dybvig (1983).

[54] *See* Hulster (2009).

losses, e.g. due to earnings-fluctuations, spillover write-offs, and macroeconomic shocks, earlier.[55] 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 analysed 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})[56], 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 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,

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

2.3.2 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

55 Spillover-write-offs refer to losses caused by the default of other financial institutions.

56 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.

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*[57]*)*: 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 2.2 demonstrates the different types of initial distributions of firm values $V_{0,i}$ along a fixed amount of N financial institutions ($N = 30 = \overline{N}$).

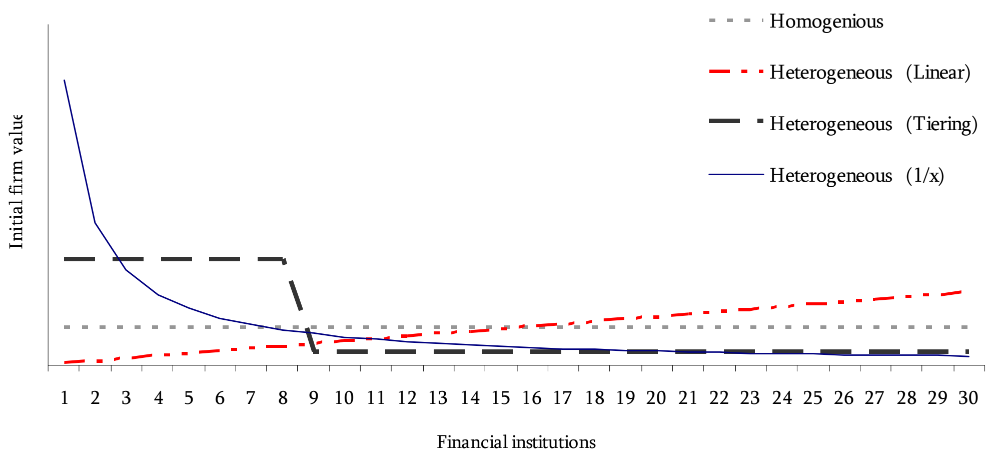

Figure 2.2: Different types of financial network structures

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 $V_{0,j} = V_{0,i}$ $\forall i \neq j$, whereas in a heterogeneous world financial institutions are starting from different initial firm values $V_{0,j} \neq$

57 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.

$V_{0,i} \quad \forall i \neq j$. (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.

2.3.3 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 $p_{ij} = 1 \ \forall i, j \in N \wedge i \neq j$ 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:

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

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 Interlinked-Asset-Vector (Y_i) represent the initial amount of assets of institution i that is borrowed from other banks. The product of the Borrower-Lender-Matrix ($X_{i,j}$) and Interlinked-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[58].

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 (2.1) has to be rewritten to

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t - W_{t,i} \tag{2.2}$$

2.3.4 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[59], 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 (2.2):

58 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.

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

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t - W_{t,i} - S_{t,i} \tag{2.3}$$

Shocks are calculated as follows

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

2.3.5 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. [60] We label this *traditional bank tax* concept with $\hat{B}_{t,i}$ and derive it as follows:

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

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 $V_{t,i}$.[61] The advantages of this alternative bank tax are that (i) the tax only needs to be paid if earnings are positive, which

[60] 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% 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.

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

does not put further pressure on troubled banks suffering from losses over the last periods, and (ii) it lowers the incentive to gamble[62].

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[63], 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[64]. This fact simplifies a 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 (2.3), resulting in:

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t - W_{t,i} - S_{t,i} - B_{t,i}, \tag{2.4}$$

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

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

62 *See* Aussenegg and Kronfellner (2011).

63 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.

64 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. $E\left[E_{t,i} - E_{t-1,i}\right] \sim 0$.

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.

2.4 Measuring and Modelling 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.

2.4.1 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 $V_{0,i}$. 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[65] future bail-outs.

2.4.2 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

[65] 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.

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:

$$dV_{t,i} = \mu_{t,i} V_{t,i} dt + \sigma_{t,i} V_{t,i} dB_t - W_{t,i} - S_{t,i} - B_{t,i} + \overline{dE_{t,i}} \tag{2.5}$$

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 ($V_{0,i} / V_0 > V_{TBTF}$):

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

(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[66]. 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.

[66] 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.

As the liquidity injection directly increases the equity of the bank, it needs to be added to the equity process function and equation (2.5) has to be rewritten (again):

$$dV_{t,i} = \mu_{t,i}V_{t,i}dt + \sigma_{t,i}V_{t,i}dB_t - W_{t,i} - S_{t,i} - B_{t,i} + \underbrace{\overline{dE_{t,i}}}_{\substack{TBTF- \\ Bail-Out}} + \underbrace{\sum_{t=\overline{t_{j-1}}}^{\overline{t_j}} B_{t,i}}_{Soft\ Bail\ Out} \tag{2.6}$$

$\overline{t_j}$ are dates of liquidity injections with $j \in (1, 2, \ldots)$, 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. $B_{t,i} = \hat{B}_{t,i}$.

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 2.3 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 $CR_{Min} < CR_{SBO} < CR_I < CR_{Max}$.

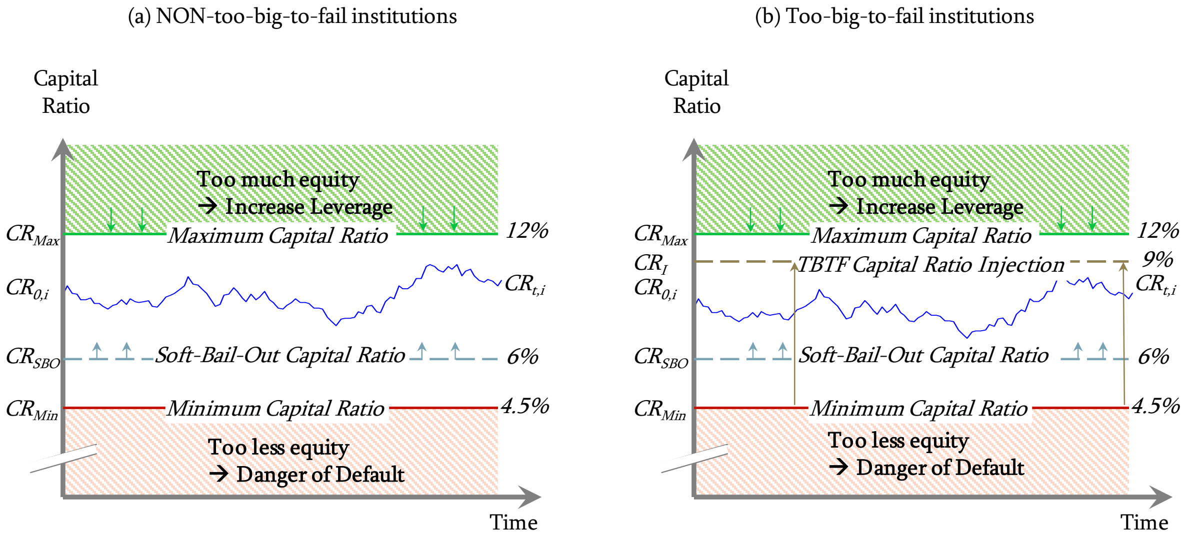

Figure 2.3: Overview of different capital ratio boundaries used in the model for (a) non-too-big-to-fail banks and (b) too-big-to-fail banks

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 2.3, 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.

2.5 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.

2.5.1 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).[67]

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 numbers of steps could be applied and would delivers 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.

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

Modelling 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[68]. 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.

2.5.2 Measuring the Contagion Effect

It is commonly known in the academic literature that contagion is *the* critical factor for financial network failures.[69] 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[70] 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 2.4 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 45%), then bail-outs are no more an option for the regulator, as the whole financial system will collapse very likely.

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68 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.

69 This is also demonstrated in the sensitivity analysis of the next chapter.

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

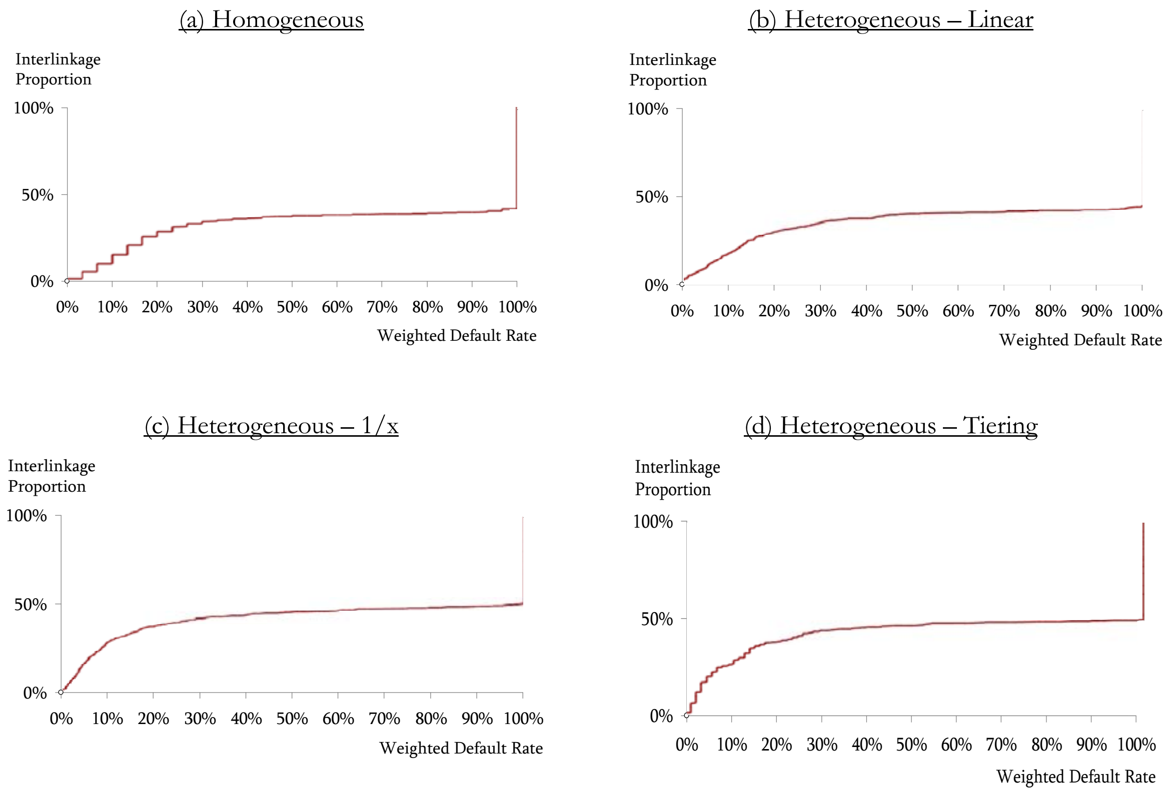


Figure 2.4: The contagion effect of different financial network structures

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 standardised 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 (2.1)) and the equity value is modelled 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).

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

2.5.3 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[71]

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 function in this analysis.[72] Figure 2.5 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 2.5, the bigger 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 ($\sigma_i = 16.2\%$) and the amount of macroeconomic shocks ($k = 13.4\%$).

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

[72] 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.

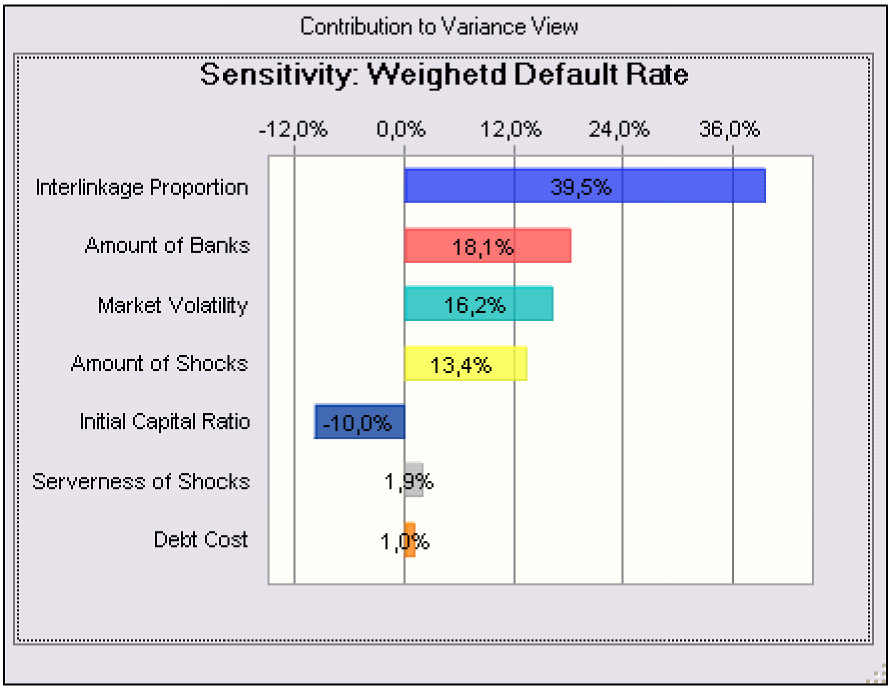


Figure 2.5: Influence of financial market parameters on the weighted default rate

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. $V_{TBTF} = 100\%$.

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 can not 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.

2.5.4 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.[73] 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[74] – of CR_{SBO} = 6%.

To provide an overview, Table 2.1 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 analysed 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)

[73] 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.

[74] 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 2.1: 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[75], 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 2.6 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 2.6 are the result of linear regressions on 10,000 data points of Monte Carlo Simulations for the two bail-out approaches.[76] The parallel shift of the two lines, indicated by the arrows in Figure 2.6, can be interpreted as reduction in government costs (C_G), whereas the costs borne by banks (C_B) are the same in both approaches.[77] In other words, under the same circumstances (bank tax and weighted default rate[78]) the new soft-bail-out concept is less costly than the traditional TBTF-

[75] We display below conomic cost changes for different (bail-out) approaches as a function of the interlinkage proportion.

[76] 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 be able to easier compare the two concepts.

[77] 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.

[78] 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.

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.

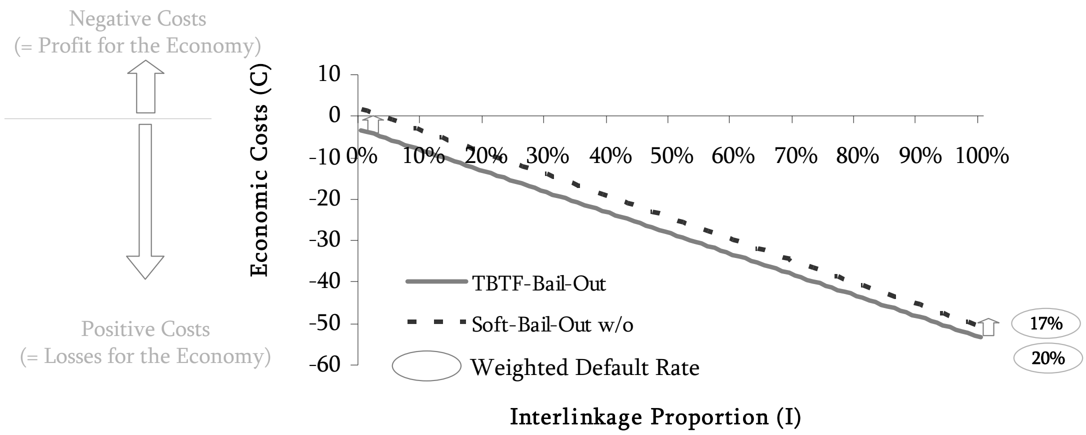


Figure 2.6: Economic costs of the TBTF-bail-out and the soft-bail-out approach (*without* connection between bank tax and the interlinkage proportion)

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-boarderline $V_{TBTF} = 5\%$; 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.

Ad (ii): In a second step we consider the connection between the alternative bank tax and the interlinkage proportion, as described in equation (2.4). Figure 2.7 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[79], 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 2.7 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 favourable in banking systems with a low degree of interlinkages between banks. The

[79] Eisenberg and Noe (2001) even describe linkages between firms as cyclical and create the term *cyclical interdependence*.

reason for this is that a lower interlinkage level generates less bank tax proceeds when the bank tax is based on the interlinkage level.

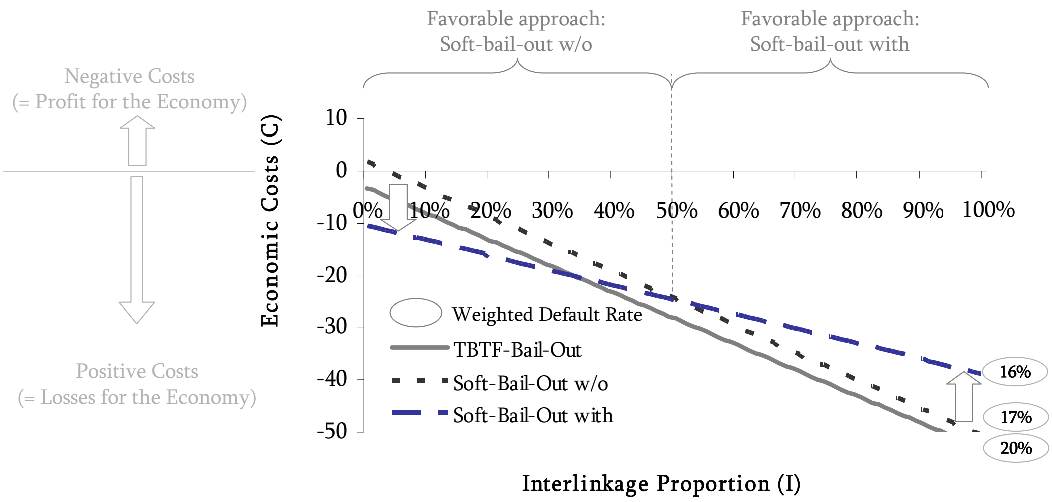


Figure 2.7: Economic costs of the TBTF-bail-out and the soft-bail-out approaches *with* and *without* connection between bank tax and the interlinkage proportion

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 2.8 and 2.9).

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 2.5 and 2.6 by circled numbers. They reveals that the TBTF-bail-out approach generates a weighted default rate of *20%*, whereas the soft-bail-out approaches generates lower rates of *17%* and even *16%*, in case the bank tax is connected to the interlinkage proportion.

2.5.5 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 2.2, 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 2.8 and 2.9. The two least influential parameters, the financial network structure and the debt costs (r_D) remain fixed. The column ´Sensitivity´ in Table 2.2 refers to the results of Figure 2.5, 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)-------		

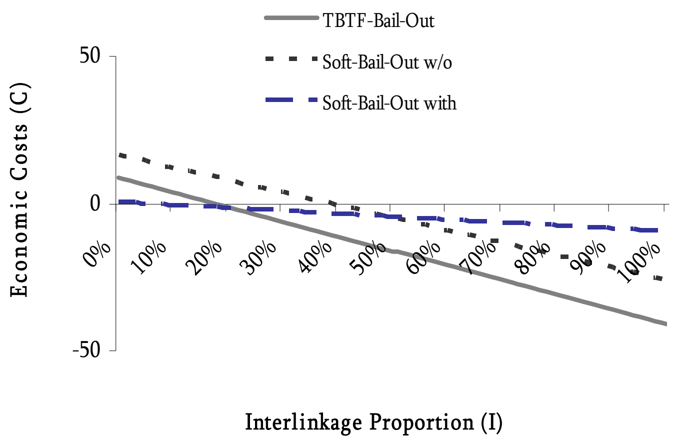
Table 2.2: Considered cases for model sensitivities

Figure 2.8 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 2.8), 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).

Figure 2.8: Model parameter sensitivity analysis: Simulation result of a best-, base-, and worst-case scenario

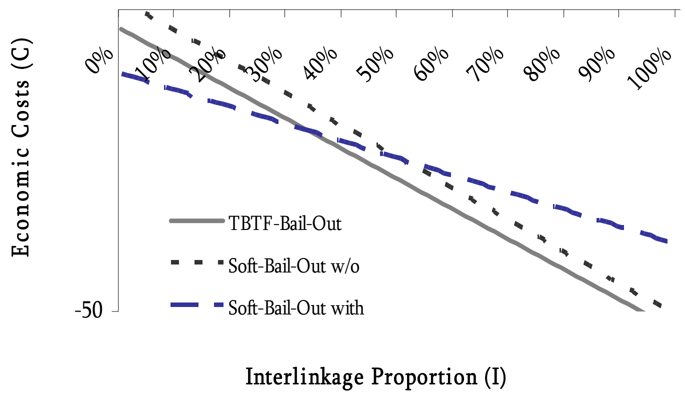
The model parameters of the **best case** are: the interlinkage proportion $I_i = 0\%, ..., 100\% \ \forall i$ (continuous), amount of shocks $k = 0$, initial capital ratio $CR = 15\%$, amount of banks $N = 10$, severity of shocks $h = 10\%$, debt costs $r_D = 0\%$. The model parameters of the **base 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



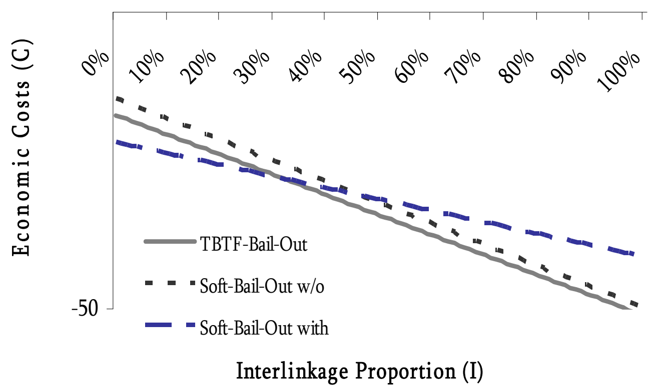
Parameters Best Case	
Amount of Shocks (k)	0
Initial Capital Requirement (CR)	15%
Amount of Banks (N)	10
Serverness of Shocks (h)	10%
Debt Costs (r_D)	0%

(b) Base case



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%

(c) Worst case



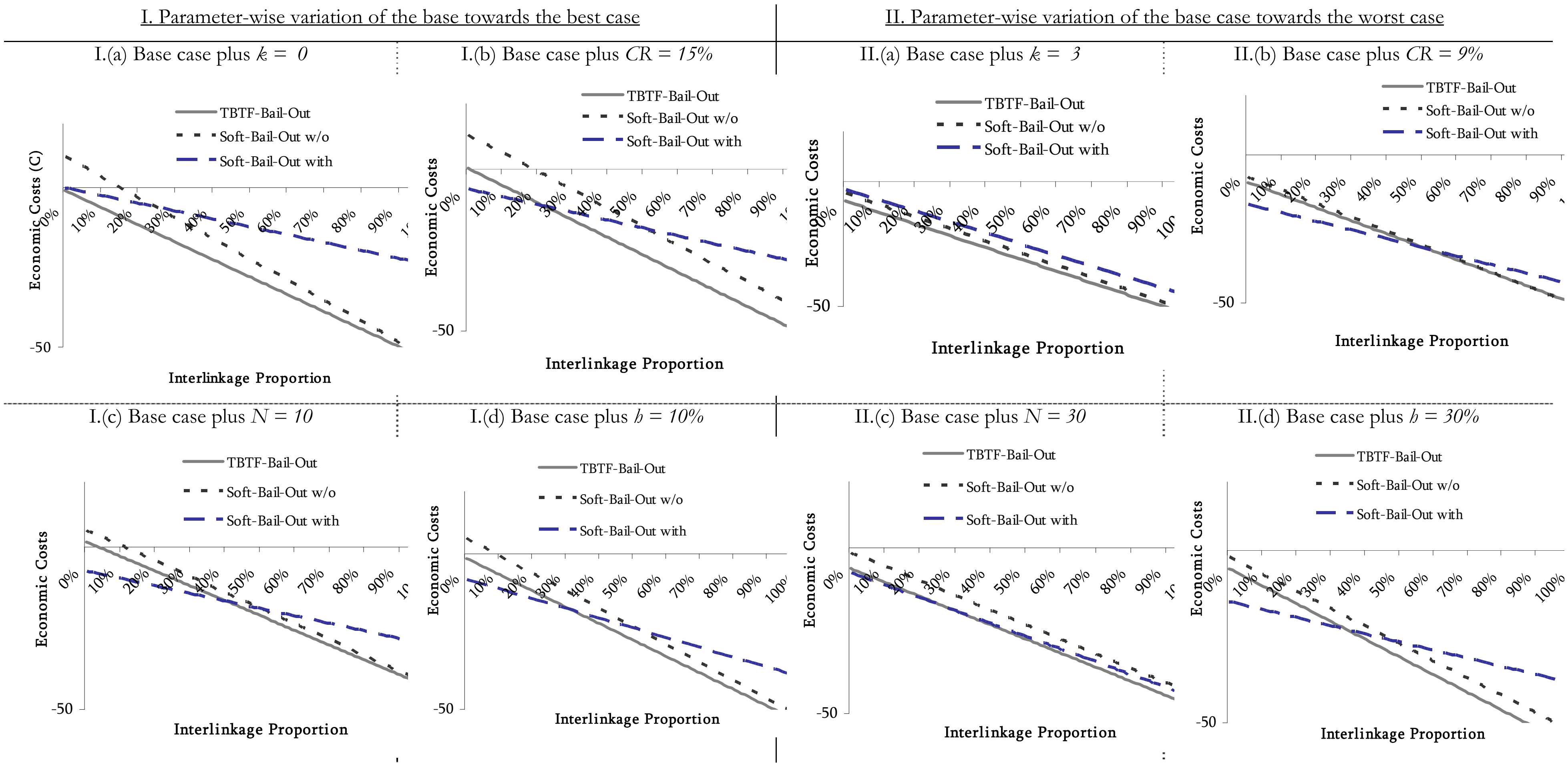
Parameters Worst Case	
Amount of Shocks (k)	3
Initial Capital Requirement (CR)	9%
Amount of Banks (N)	30
Serverness of Shocks (h)	30%
Debt Costs (r_D)	5%

Furthermore, we analyse the effect of changing only one parameter from the base case in Table 2.2 to the best- or worst-case. Figure 2.9 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 2.9 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).

Moreover, in all cases (see Figure 2.8) *and* (parameter-wise) variation of the base case (see Figure 2.9), the weighted default rates (Ω) of the soft-bail-out concepts are better than for the TBTF-concept, the current best practice.

Figure 2.9: Model sensitivity checks: Parameter-wise variation of the base case

Consideration of parameter-wise variation of the base case, as illustrated in Table 2.2. 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.



2.6 Summary

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 dissertation 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 dissertation, we want to mention the following additional ideas: first, a cyclical modelling 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 modelling with stochastic processes and calculation of risk weighted assets would be possible.

Chapter-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

3 Alternative Bank Tax Modelling to Increase Bank Stability

3.1 Introduction

Companies are used to estimate their expected returns properly and to assess the associated risk of projects and future business strategies. In contrast, the risk taking practice in the banking industry is different. After the turmoil (because of the sub-prime crisis and finally of the collapse of Lehman Brothers in September 2008) and in order to prevent an even more severe financial collapse, public authorities learned that they have to support all ´Systemically Important Financial Institutions´[80]. Since the bankruptcy of a large (i.e., too-big-to-fail- or too-interlinked-to-fail-) bank, such as Lehman Brothers, can do tremendous harm to the whole economy (locally and, because of the interlinked financial market, globally), central banks are usually playing the Lender of Last Resort (LoLR)[81]. This function is necessary to prevent the withdrawing of huge amounts of money. Theories of bank runs and the role of central banks to stabilize the banking system date back to Bagehot (1873), who was the first analyzing these monetary mechanisms and came up with the term ´LoLR´.[82]

Knowing the role of central banks as the LoLR, financial institutions inevitably expect to be bailed out by the government in case of a threatening default. ´Of course this commitment is a disaster in terms of moral hazard…´.[83] As a result, bank managers take more risks than managers of other industries do. Moral hazard is the first of two main reasons why bank managers act in terms of risk assessment (of its projects and business strategies) with a higher risk appetite than managers in other industries. The second reason for a higher risk-appetite in the financial industry is the high proportion of profit-related bonus payments for managers. With the theory of option-pricing and -hedging, we show how this bank-specific compensation scheme even further enhances the risk appetite of bankers.

80 *See* Freixas and Rochet (2010).
81 In the related literature (such as Freixas and Rochet (2008)), this term is mostly used to describe the bail-outs of banks as the last possibility to prevent such a contagion that might spread over to the whole industry, and even to the real economy, as we have experienced in this financial and economic crisis.
82 *See* Tucker (2009).
83 *See* Freixas and Rochet (2010).

Recent contributions to the discussion of how to stabilize banks provide a large variety of different ideas. For example, Admati and Pfleiderer (2010) propose a model to solve the too-big-to-fail-problem by holding more equity.[84] They argue that before the financial crisis broke out, poor leverage ratios (with equity as low as 1% to 3% of total assets) caused server troubles to almost all financial institutions. Even a slight loss can dispatch the small equity capital base of such institutions. Although financing through equity is more expensive compared to debt financing, they document in their model that an equity base of 25% to 30% of total assets would improve the current situation of fragile banks and would reduce social costs of potential future bail-outs.

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. In addition, Rochet (2009) puts forward the proposal to centralize not only the derivatives and repo market but also the unsecured interbanking markets, such that banks would have to choose between the centralized and supervised market and the private OTC interbanking market. Many of these ideas are somehow considered in the Basel III Accord, in additional bank taxes, and other stability mechanisms. Nevertheless, risk-affine banks tend to gamble and financial regulators all over the world are trying to establish mechanisms to prevent banks from doing so.

In this dissertation we address the two hardly separable issues of moral hazard and positive incentives in the financial industry towards risk taking due to remuneration-schemes. In other words, we provide a model to potentially decrease managers´ and creditors´ appetite to gamble. *For managers*: Current performance related remuneration schemes can be interpreted as a long call option on the profit, i.e., on the increments of the firm value. By boosting profit volatility, managers are able to increase the price of their own remuneration call option. This has a negative effect on the firm value and even the solvency of the organisation. *For creditors*: As a result of state aid for banks, the de-facto and already anticipated public bail-out guarantee can be interpreted as a long put option for creditors on the firm value that reduces the funding costs for banks.

Besides the two main objectives to reduce manager's risk taking and to equalize moral hazard in the financial industry, our new mechanism also addresses the main critics of the current

[84] This argument is also mentioned in the Financial Stability Report 2010 of the Austrian National Bank (OeNB) – The Economics of Bank Insolvency, Restructuring and Recapitalization.

regulatory system, recently evoked in the academic literature.[85] In order to prevent or flatten future financial crises, regulators need to establish a new mechanism[86] with the following characteristics:

(i) penalizing tremendous growth or restructuring, i.e., the high risk appetite by bank managers
(ii) lowering the reliance on capital-requirements, leverage-ratios, and interest rates to regulate the financial system
(iii) harmonizing the treatment of sound and non-sound banks
(iv) lowering the inequality and moral hazard emerged by governmental bank bail-outs
(v) applying this mechanism internationally with less possibility of national adaptations

Our mechanism uses barrier put options[87] to protect the downside of the bank´s payoff function. Periodically, banks should be (legally) obliged to acquire such put options from the state. The premium of the put options can be seen as a bank tax alternative. However, in contrast to current bank tax approaches, this bank tax approach even helps banks far before their definite insolvency as the protection put options increase in value when banks tend to approach default and, thus, increase the firm value. Hence, these put options can be seen as mini-bail-outs in advance, financed by the banks, that prevent costly bail-outs in case of complete insolvency.

The remainder of this chapter proceeds as follows: First, we focus in section 3.2 on the decision making process of managers in financial institutions to understand the drivers of recent excessive risk-taking in the banking industry. Second, based on the understanding of this risk-taking in the banking sector, we elaborate in section 3.3 a new mechanism to curtail banks risk-taking and to strengthen the soundness of banks. Third, in section 3.4 we present numerical results of our new mechanism and compare them to the current best practice. The added financial stability is analysed via Monte Carlo Simulation using a simplified financial market model. Finally, section 3.5 concludes.

85 The related academic literature puts forward the following critics on the current regulatory system: (i) focussing on reserve-, capital, and leverage ratios is not enough (see Atkinson and Blundell-Wignall (2009), analysing the case of Northern Rock), (ii) no instrument addresses the risk of intensive growth and restructuring (see Rajan (2005)), (iii) the current monetary policy is a too blunt instrument to prevent future financial crises (see European Central Bank (2010), Lahard (2008), and Bruni (2009)), (iv) the treatment of distressed financial institutions has to be harmonized (see Dewatripont et al. (2010)), and (v) due to moral hazard, banks can be certain to get a bail-out by the state (see Freixas and Rochet (2010)).

86 The idea of a new mechanism is also postulated by Dewatripont et al. (2010), even though the characteristics of a feasible new mechanism are not derived as precisely as in this dissertation.

87 We are calling these long barrier put options from now on ´protection put options´.

3.2 Explaining the Excessive Risk-Taking of Banks

As mentioned in the previous chapter, we contribute, to the current regulatory discussion by suggesting a new regulatory mechanism. This mechanism could prevent excessive risk taking in the financial industry, equalize moral hazard, and further stabilize banks. In order to do so, we firstly need to properly understand the reasons for the highly distinct risk appetite in banking.

The financial collapse has proven rigorously that the current regulatory regime is not able to prevent banks from excessive risk-taking. In the related literature, researchers from different finance-related academic areas mostly describe the following points as the main aspects why banks have a higher risk appetite (or sometimes even ignore the volatility of their returns or assets) than other industries[88]:
- *Moral hazard* fosters decisions towards riskier business models since the government as the Lender of Last Resort (LoLR) guarantees the solvency and bails-out too-big-to-fail or system relevant financial institutions.
- *Compensation-schemes* of managers with – compared to other industries – a high proportion of profit-related bonus-remuneration.[89]
- *High competition* due to, relatively to other industries, interlinked and fast moving markets furthermore enhances risk-taking and, thus, threatens financial stability.[90]

3.2.1 Modelling Financial Institutions

Before we generate a new mechanism, we need a model to describe the main characteristics of a financial institution that can be altered by managers and/or by creditors, that might influence managers. Along with the Merton Model (1974), we assume that the firm value V_t of a financial institution follows a stochastic process. The organisation is financed by equity E_t and debt D_t, and the firm value at time t is the sum of the equity- and debt-process, i.e., $V_t = E_t + D_t$, with $0 \leq t \leq T$. (Note that due to this equation the firm value process changes automatically if the equity process alters.)

[88] *See* Freixas and Rochet (2008) or Dewatripont et al. (2010).
[89] The related literature to compensation packages distinguishes between three types of compensation: salary, performance related bonus and stock-based incentives. See, e.g. Tirole (2006) or Smith and Watts (1982).
[90] *See* Allen, Gale (2000) and Freixas and Rochet (2008).

The company borrows a certain amount of money D in $t=0$ and pays back at time $t=T$ $D_T = D e^{r_D T}$, where r_D is the borrowing yield and no further debt is outstanding or will be issued within the timeframe $[0,T]$. Two cases can occur at maturity T:

(i) $D_T \leq V_T$: the firm is solvent and still has equity $E_T = V_T - D_T$,

(ii) $D_T > V_T$: the firm is insolvent and the bond holders only get V_T after asset liquidation.

Figure 3.1 illustrates the development of the three processes D_t, E_t, and V_t in the interval $[0, T]$ with the two possible scenarios (i) solvency and (ii) default.

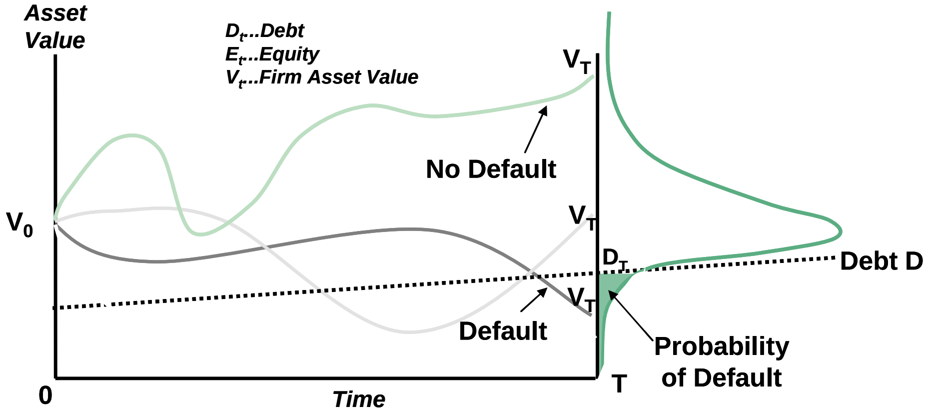


Figure 3.1: Stochastic process of the firm value Vt, the debt value Dt, and probability of default according to the Merton Model

At maturity two cases can occur. (i) $D_T \leq V_T$: the firm is solvent and still has enough equity $E_T = V_T - D_T$, and (ii) $D_T > V_T$: the firm is insolvent and the bond holders only get V_T after asset liquidation. This implies, that the payoff of the firm value at maturity equals the payoff of a European Call Option $\max(0, V_T - D_T)$, and the payback of the firm to the bond holder is $\min(D_T, V_T)$.

Assuming that the firm value develops according to a Geometric Brownian Motion[91], it immediately can be seen that the default probability of the bank is increasing in volatility σ_V, which is perfectly in line with economic intuition. The higher the fluctuation of the firm

[91] The Geometric Brownian Motion is modelled by $dV_t = \mu_V V_t \, dt + \sigma_V V_t \, dW_t$ with a constant drift parameter μ_V, volatility $\sigma_V > 0$, and a standard Brownian motion W_t.

value, the higher the risk that the firm value falls below the debt value ($V_T < D_T$). Thus, the Merton Model demonstrates that a lower volatility of the firm value decrease the default probability.

3.2.2 Modelling the Risk Appetite of Managers and Creditors

In contrast to the result of Merton that an increasing firm value volatility σ_V debases the financial situation of a firm, we will show that the contrary is true for *managers* bonus payments. It is in favour of managers when the firm value volatility σ_V increases as their remuneration can be interpreted as a call option on the banks firm value[92]. The higher the volatility, the more valuable the call option.

Creditors, borrowing the amount D to the bank at time $t=0$, are holding a short put option with strike price D_t. The idea that creditors are holding a short put option on the banks assets stems from Merton (1974) and is later used, e.g. by Wilson (2010) who describes the incentive of selling assets. Additionally, creditors of large institutions can be (almost) certain that in case of default the state bails out the bank. Hence, this de facto guarantee by the state can be seen as a second option, owned by the creditors. This second option is a long put option on the bank with strike price D_t. (However, this only applies to banks that are systematically relevant and, thus, too-big-to-fail.) Consequently, for large institutions, creditors are risk-neutral as their short put and their long put option cancel out each other. In contrast to smaller banks or other industries, where creditors are not (or too a much lesser extent) holding such a second put option, creditors of large financial institutions have less incentives to put pressure on managers to limit their risk-taking.

[92] The usage of a long call option is a widely-spread practice of executive remuneration to motivate/control managers. When classical research contributions on managerial remuneration schemas (such as Carpenter (2000)) discuss the utilization of call options, they refer to a call option as an already issued security that is given to managers (according to their performance). In contrast to the consideration of a call option as a security, we use the term call option to describe the relationship between profit and in cash-paid bonus.

3.2.2.1 Analysing the Reasons for the Enhanced Risk Appetite of Managers

In the following, we build on the approach of Merton (1974) to model the asset fluctuation of a company as a Geometric Brownian Motion with identically independent distributed increments. These increments are interpreted as profit per period. We study the nature of bonus payments under the assumption that the managers only want to maximize their compensation and that bonus payments are only paid if the company has a positive profit r_t. Since the profit of a company largely determines the returns of its stock, we model the profit r_t analogous to a classical return distribution on the stock market:[93]

$$r_t \sim N(\mu_r, \sigma_r) \tag{3.1}$$

Figure 3.2 illustrates the relationship of firm value and profit per period r_t *without* manager bonus. Note that a default occurs as soon as a negative increment ΔE_t (change in equity value) is bigger than E_{t-1} (equity value at the end of the previous period).

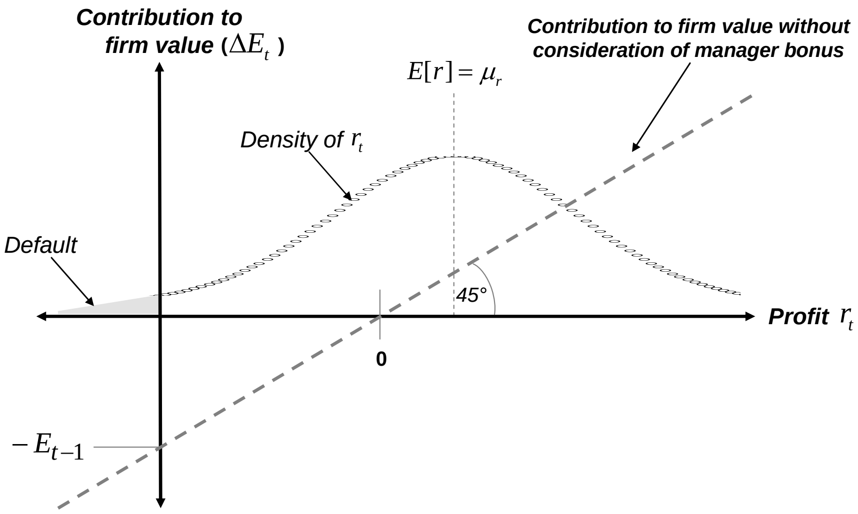


Figure 3.2: Profit (r_t) density and change in firm value without manager bonus

[93] In order to keep the model at this stage as simple as possible, we knowingly neglect scientific theories of fat tails, asymmetric skewness, etc. in the return distribution of r_t.

We further assume that bonus payments to managers (*Bon$_t$*) are defined as a particular proportion $b \in [0, 1]$ of the profit r_t. Consequently, bonus payments and the contribution to the equity value (ΔE_t) (and, thus, to the firm value (ΔV_t)) can be written as:

$$Bon_t = Max(r_t \cdot b,\, 0)$$

$$\Delta E_t = E_t - E_{t-1} = r_t - Bon_t$$

$$\begin{aligned} \Delta V_t = \Delta E_t + \Delta D_t &= \underbrace{r_t - Bon_t}_{\Delta E_t} + \underbrace{D \cdot e^{r_D \Delta t}}_{\Delta D_t} = \\ &= \underbrace{\mu_r V_t\, dt + \sigma_r V_t\, dW_t - Bon_t}_{\Delta E_t} + \underbrace{D \cdot e^{r_D \Delta t}}_{\Delta D_t} \end{aligned} \tag{3.2}$$

Figure 3.3 shows that the bonus payments in our model are comparable to a call option on the firm´s profit, with *b* as profit participation factor[94]. The participation factor indicates how much of the (positive) profit is skimmed by managers.

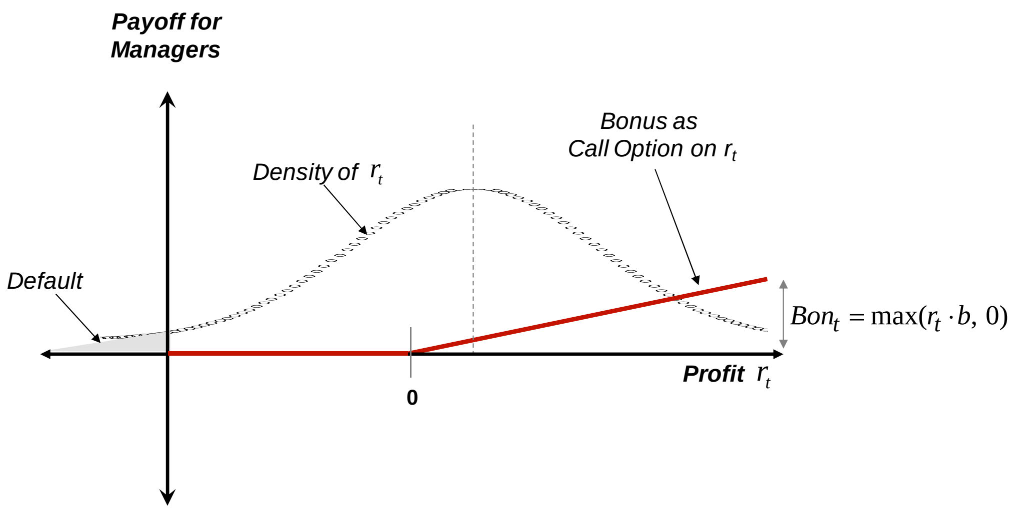


Figure 3.3: Bonus payoff for managers as a call option on the profit r_t, with *b* as profit participation factor

The increment of the equity value (ΔE_t) in equation (3.2) can be rewritten as

[94] The participation factor *b* indicates how much the value of the call option changes if the profit r_t changes by 1 currency unit in case of a positive profit (i.e., r_t > strike price = 0).

$$\Delta E_t = r_t - Max(r_t \cdot b, 0) = r_t - b \cdot Max(r_t, 0) \tag{3.3}$$

Figure 3.4 exhibits the mismatch concerning the use of the profit r_t. A positive profit lowers the equity contribution to the firm value with the factor $[1-b]$, whereas firm´s equity absorbs a negative profit with a factor of 100 %. This modelling of the profit skimming is perfectly in line with a statement by Stiglitz (2010) that ´…bankers shared in the gains but not in the losses.´ The thick (red) line indicates the positive or negative contribution to ΔE_t and, thus, to ΔV_t, showing a sharp bend at $r_t = 0$.

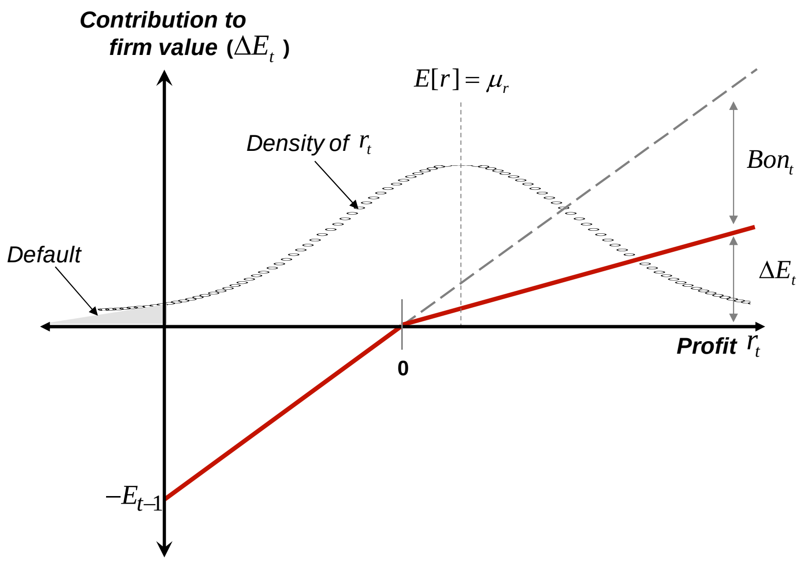


Figure 3.4: Profit r_t and its contribution to equity and firm value

At this point, one has to note that the part $Max(r_t, 0)$ in equation (3.3) can be interpreted as call option on the profit r_t with a strike price of zero and c_T as price at maturity T. In other words, managers are holding a long call option on the periodic profit r_t with a payoff structure of $b \cdot Max(r_t, 0)$. Any pricing method for options (for instance the Black-Scholes formula) reveals the positive effect of a higher volatility to the value of a long call option c_t. In mathematical terms, the option price sensitivity to movements in volatility of the underlying, the vega, is positive. Consequently, our bonus payments (Bon_t) have also a positive vega:

$$Vega_{Bon_t} = \frac{\partial Bon_t}{\partial \sigma_V} > 0$$

According to the mismatch of profit sharing and the positive vega, managers are able to boost the value of their long call option on the profit r_t by taking more risk. Especially large banks are facing this moral hazard problem due to (i) expected governmental bail-out and (ii) a high profit-related remuneration across industries[95].

3.2.2.2 Analysing how creditor´s bail-out guarantee fosters risk taking

Compared to bonus payments, the changes of creditors´ incentive schemes due to moral hazard are not explicitly expressed in equation (3.2). The fact that creditors of too-big-to-fail banks are receiving a bail-out guarantee (*BOG*) from the state is implicitly priced in the interest rate r_D for borrowing *D*. The debt amount *D* equals the present value of the zerobond and *BOG* corresponds to a long put option on the firm value with *D* as strike price. If the state assures the solvency of banks in the case of a default, the risk for creditors is smaller and, thus, the bank is obtaining cheaper funding than it might get without *BOG*. Consequently, this mismatch has to be equalized by the bank (and not by the creditors) as it is a distortion in competition towards smaller banks or other industries that do not obtain an additional state aid in the form of a *BOG*.

We define $r_{D,\,wo}$ as the hypothetic interest rate without *BOG*. The advantage of the *BOG* is then the difference between the actual funding rate (r_D) and the hypothetic interest rate without *BOG* ($r_{D,\,wo}$). Thus, the value of the funding difference $\Delta r_D^{\ T}$ determines the value of the *BOG*:

$$BOG = D \cdot \underbrace{\left((1 + r_{D,\,wo})^T - (1 + r_D)^T \right)}_{\Delta r_D^{\ T}}$$

95 *See* e.g. Glinavos (2011) or Stiglitz (2010).

As the hypothetic interest rate without *BOG* ($r_{D,\,wo}$) can not be observed, we approximate the *BOG* by the value[96] of a put option (p_t)[97] on the firm value with the outstanding debt *D* as strike price.[98]

$$BOG = D \cdot \Delta r_D^{\;T} = D \cdot p_t \tag{3.4}$$

In other words, the *BOG* equals the interest rate difference over the observation period due to a smaller risk premium. It also equals a long put option on the firm value with strike price *D*. Figure 3.5 illustrates how the payoff for creditors changes when a BOG is incorporated in the payoff function.

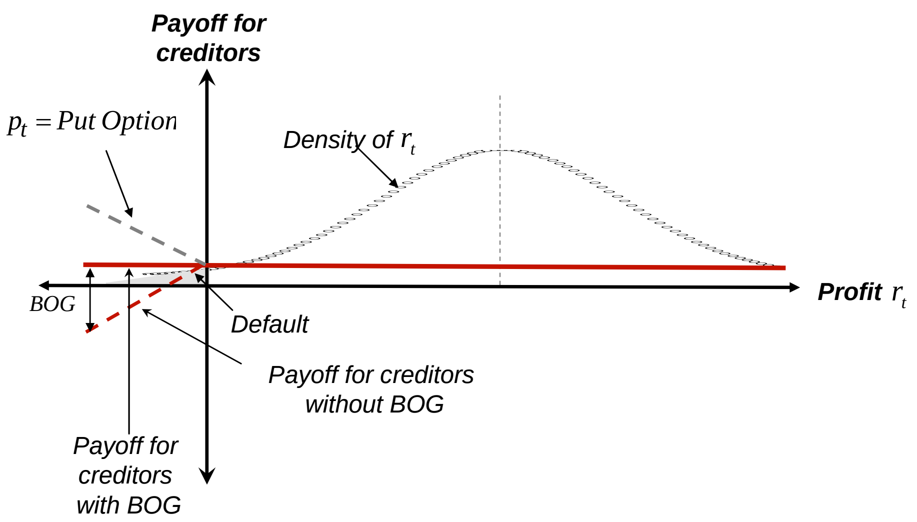


Figure 3.5: Payoff for creditors with and without a state bail-out guarantee (*BOG*). The BOG can be interpreted as long put option on the firm value

To understand the potential influence of the owner of the *BOG* (the creditors) on bank managers, we are analysing in a next steps the sensitivity of creditor´s payoff structure. Analogous to bank managers we are using vega to understand the risk appetite of creditors.

96 We use as price of the put option a percentage fraction of *D*.

97 Note that the long put option p_t to price the BOG (see Figure 3.5) is different from the long put option P_t that is used for protection purposes.

98 The price of the long put option can be calculated by any adequate pricing method, such as the Black-Scholes-Model.

Creditors of non-bank companies or (smaller) banks without state *BOG*, only hold a short put option on the firm value with D as strike price. Thus, their vega is negative:

$$Vega_{Short\ Put} = \frac{\partial Short\ Put}{\partial \sigma_V} < 0$$

Consequently, creditors of non-bank companies or smaller banks have the incentive to limit the risk appetite of managers. In contrast, creditors of too-big-to-fail banks are holding – additionally to the short put option – a long put option (the BOG). As the two options cancel out the overall vega is zero:

$$Vega_{Short\ Put\ +\ BOG} = \frac{\partial (Short\ Put + BOG)}{\partial \sigma_V} = 0$$

Thus, creditors of large financial institutions are perfectly hedged against volatility risk and, therefore, have no incentives to control the risk taking of bank managers.

Considering both effects, (i) the profit skimming by bank managers with a call option (see Figures 3.3 and 3.4) and (ii) the bail-out guarantee (*BOG*) of large financial institutions that can be approximated by a long put option (see Figure 3.5), the contribution of the profit r_t to the firm value is illustrated in Figure 3.6:

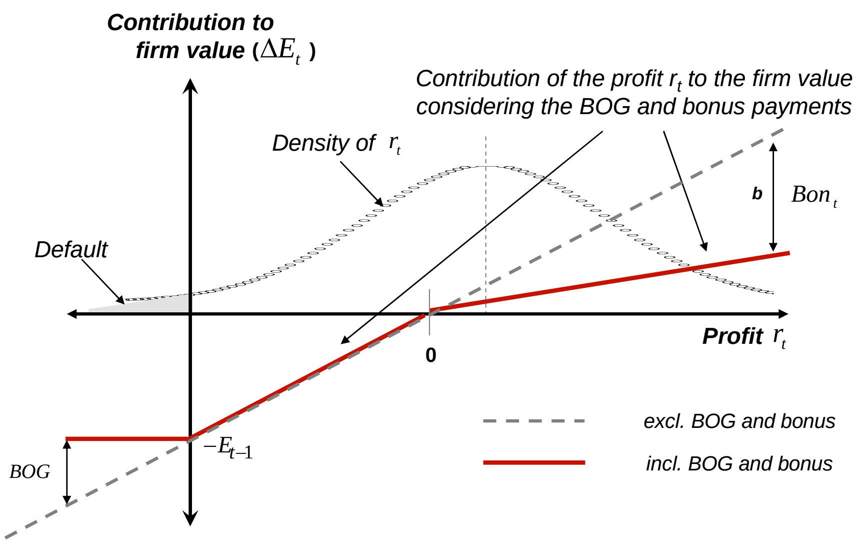


Figure 3.6: Contribution of the profit to the firm value considering bonus payments and *BOG*

To summarise, managers of large financial institutions have an incentive to hold up (or even further increase) the volatility of the firm value. In addition, the risk taking of bank managers is not limited by their creditors as creditors of such institutions are indifferent concerning manager´s risk taking. These effects are amplified especially in the financial industry due to (a) moral hazard, (b) global-wide competition and (c) a remuneration system with a high proportion of performance related bonuses.

3.3 A New Model to Increase Financial Stability

In order to reduce banks incentives to gamble, a new mechanism is necessary to punish the excessive risk taking by bank managers, as they are – in case of large banks – not controlled by creditors.

3.3.1 Reduction of the Risk Appetite of Managers

As the positive long volatility exposure of managers is responsible for their risk taking, the idea is to (partly) hedge the vega risk by spending (part of) the bonus (stemming from a positive profit r_t) on buying a hedging instrument. Among a large variety of derivative instruments, an appropriate way to hedge the positive vega of managers is to buy long put options (P_t) and to implement them in their payoff profile. In order not to further interlink the financial system, this protection put options are issued by the state. The premium of the put options is a bank tax alternative that is used to directly stabilizing the soundness of the bank. In this model, each bank pays bank tax according to their probability to get bail-out by the state. Compared to current bank tax approaches, this bank tax mechanism, first, decreases the probability of bank bail-outs as the implementation of put options in a banks payoff structure hedges losses and, thus, increases the distance to default in stress-scenarios. Second, this new bank tax mechanism represents an answer to the discussion of how to use a bank tax efficiently and without any inequalities between different institutes as each bank pays bank tax according to their own distance to default.

For each bank the protection put options (P_t) are financed by:

(i) a bonus reduction of h_t percent of the price of the call option c_t for managers, and

(ii) a funding cost payback (ΔBOG) from the bank of f_t percent of p_t.

Both amounts, (i) and (ii), are used to buy protection long put options from the state (P_t). Integrating these two parts of financing the put option into equation (3.2) yields

$$\Delta E_t = r_t - \underbrace{b \cdot \overbrace{Max(r_t - 0, 0)}^{Long\ call\ on\ profit}}_{Bon_t} - \underbrace{(f_t \cdot \Delta BOG) \cdot P_t}_{\substack{Buying\ new\ proctection\ put, \\ bank\ contribution\ only}} + \underbrace{(h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG) \cdot \overbrace{Max(0 - r_t, 0)}^{Long\ Put\ P_{t-1}}}_{Owing\ protection\ put\ P_{t-1}} \tag{3.5}$$

Dependent on whether the profit r_t is positive, negative, or equal to zero, equation (3.5) equals:

$$\Delta E_t = \begin{cases} r_t - \underbrace{b \cdot \overbrace{Max(r_t - 0, 0)}^{Long\ call\ on\ profit}}_{Bon_t} - \underbrace{(f_t \cdot \Delta BOG) \cdot P_t}_{\substack{Buying\ new\ proctection\ put, \\ bank\ contribution\ only}} & if\ r_t > 0 \\ r_t - \underbrace{(f_t \cdot \Delta BOG) \cdot P_t}_{\substack{Buying\ new\ proctection\ put, \\ bank\ contribution\ only}} & if\ r_t = 0 \\ r_t + \underbrace{(h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG) \cdot \overbrace{Max(0 - r_t, 0)}^{Long\ Put\ P_{t-1}}}_{Owing\ protection\ put\ P_{t-1}} - \underbrace{(f_t \cdot \Delta BOG) \cdot P_t}_{\substack{Buying\ new\ proctection\ put, \\ bank\ contribution\ only}} & if\ r_t < 0 \end{cases}$$

The already bought protection put option from the previous period is labelled by P_{t-1}. (The price of the long put option (P_t) with strike price V_{t-1} can be derived by any adequate pricing method.) According to the objective to reduce the risk taking of managers, the higher the profit the higher the contribution of managers. In contrast, the contribution of the bank to the protection put option is kept constant and depends on the initially calculated *BOG*, i.e. the value of the long put option (p_0). The periodical contribution of the bank to equalize the inequality is labelled by ΔBOG and is kept constant within the whole observation period. In case of a *loss* (negative r_t), the long put option P_{t-1} bought in the previous period *(t-1)* increases and can, thus, be seen as a hedge or protection against losses. New protection put options (P_t) are bought and financed only by the funding payback ΔBOG. The amount of new put options is $f_{t-1} \cdot \Delta BOG$. In case of a *profit* (positive r_t), apart from the contribution of the funding payback $f_{t-1} \cdot \Delta BOG$, the put option is mostly financed by a bonus reduction of $h_{t-1} \cdot b$. (As the contribution of bank managers to the protection put option does not lower the profit of the bank, but is taken from their bonus, this part of the contribution is consequently not included in equation (3.5).)

Graphically, the payoff of the protection put option (with a profit participation of $h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG$) can be drawn as indicated in Figure 3.7.

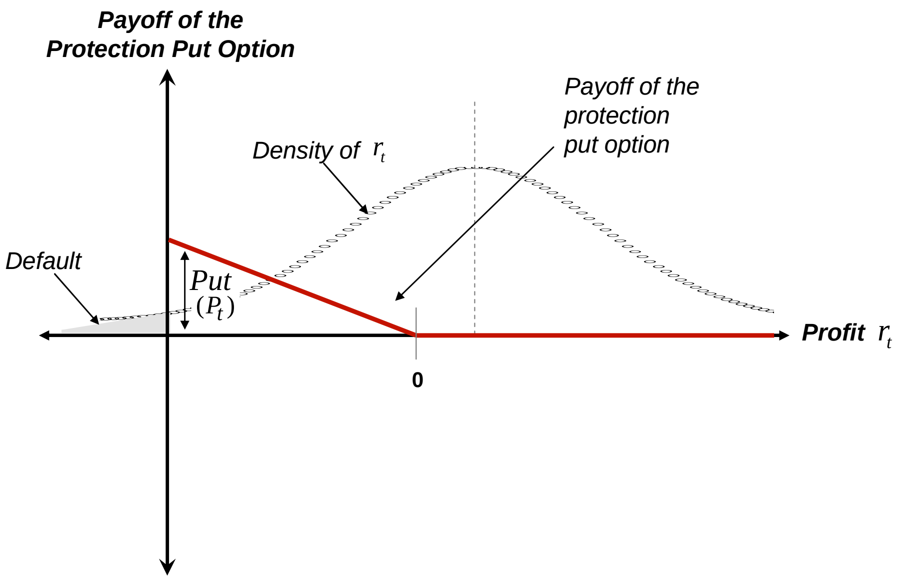


Figure 3.7: Payoff of the protection put option (P_t) with profit participation

$$h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG$$

Integrated in the payoff function of the bank, the protection put option reduces the losses in case of a negative return, as illustrated in Figure 3.8. Furthermore it decreases the volatility of ΔE_t.

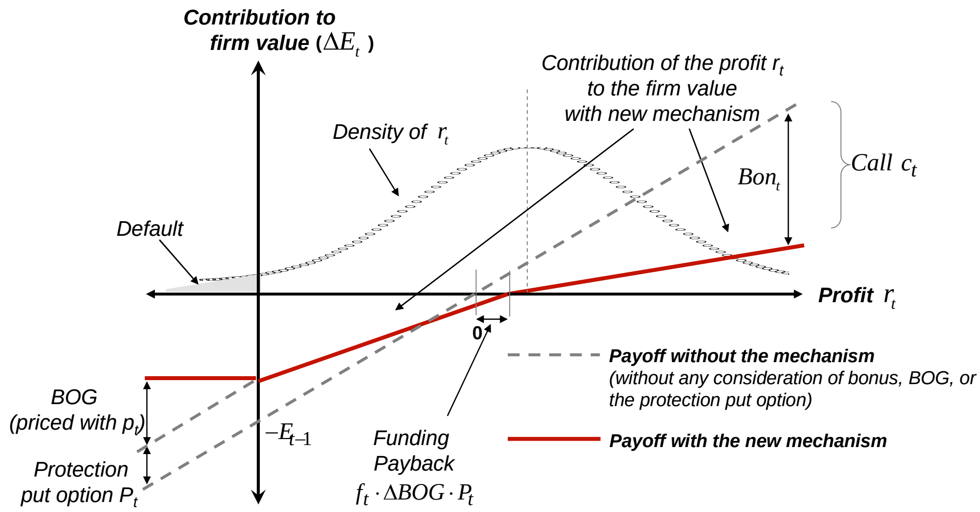


Figure 3.8: Payoff for the bank with and without consideration of the new mechanism

Switch of incentives for managers evoked by the new mechanism

If $h_t=1$ the hedge is perfect[99], no more volatility risk is involved in the payoff function of the bank and the managers have no incentives any more to take risks. Expressed ´in Greek´ the payoff-function of r_t and ΔE_t is then vega-neutral[100]

$$Vega_{Bon_t} = \frac{\partial(Bon_t)}{\partial \sigma_V} = 0$$

Thus, the higher the risk taken by managers, the more they earn from their remuneration call options *and* the more they have to pay for buying the protection put option. This decreases their risk appetite and, as it will be shown later on, increases the expected firm value V_t. Furthermore, given the put-call-parity with plain-vanilla call (c_t) and put (P_t) options and the strike V_{t-1},

$$c_t - P_t = V_t - V_{t-1} \cdot e^{-E[r_t]},$$

one easily can see that even though managers are risk-neutral by hedging vega risk, they still have incentives to boost the expected return $E[r_t]$, as they are benefiting from a high c_t.

99 In this case the protection put option P_t is mostly financed by reducing bonus payments.
100 This holds true as the vega of the put and the call are equal.

To conclude, by implementing a complete vega-neutrality for managers, we achieve the switch from an incentive scheme favourising risk taking to a scheme only focusing on expected return.[101]

Added value to the company: a higher drift and lower volatility

Without this mechanism, managers receive a call option financed by the company and its equity increments (see equation (3.3)). Incorporating protection, the put option equalizes this asymmetry analogously as it is funded especially by managers, but completely benefits the company.

The additional value consists of two parts: (i) a higher expected residual profit (changes in equity value) $E(\Delta E_t) > E(\Delta E_t^{wo})$ and (ii) lower risk $\sigma_{\Delta E_t} < \sigma_{\Delta E_t^{wo}}$ which directly leads, according to the Merton Model (1974), to a smaller probability of default. ΔE_t^{wo} refers to the profit contribution for the equity value without the new mechanism. In the appendix we proof that both, (i) a higher expected return and (ii) a lower volatility holds for the new mechanism.

3.3.2 Equalizing the Bail-Out Guarantee Owned by Creditors

Even though the creditors of (too-big-to-fail) banks are holding the bail-out guarantee (*BOG*), the competition on the funding market forces them to pass this advantage to the bank. The lower default risk due to the *BOG* is, consequently, priced in the risk premium of the offered funding rate r_D (see equation (3.4)). As derived in section 2, this funding advantage, i.e. the value of *BOG*, has to be equalized by the bank and is, thus, integrated in the new mechanism.

The idea is to reduce the profit contribution to the equity value ΔE_t by the value of the *BOG* at time *t=0*, which is equal to the price of a plain vanilla put option p_0 over the observation period *T* with a strike price of $D \cdot e^{r_D T}$. At time *t=0* the creditors lend *D* to the bank with maturity *T*. In this mechanism the funding advantage (due to $r_D < r_{D,wo}$) is equally distributed over the observation period *T*. ΔBOG is the constant equity contribution reduction in every

[101] The hedge ratio h is an indicator of the magnitude of this switch.

period (see equation (3.4)) and can be calculated using the equation of the sum of geometric series: [102]

$$
\begin{aligned}
&(\ldots((((p_0 - \Delta BOG)\cdot(1+r_D) - \Delta BOG)\cdot(1+r_D) - \Delta BOG)\cdot(1+r_D) - \Delta BOG)\ldots) = 0 \\
&\Leftrightarrow p_0 \cdot (1+r_D)^T = \Delta BOG \cdot \sum_{i=0}^{T}(1+r_D)^i \Leftrightarrow \Delta BOG = p_0 \cdot (1+r_D)^T \cdot \frac{(1+r_D)-1}{(1+r_D)^T - 1}
\end{aligned}
\tag{3.6}
$$

Note that p_0 refers to the plain vanilla long put option that is used to price the *BOG* at the beginning of the observation period[103]. The reduction of the periodical profit (r_i) eliminates the distortion of competition that the state only bails out system relevant banks and, thus, reduces only their funding costs. We recommend regulators to instruct banks to use this equalising amount of money (i.e. ΔBOG) in order to reduce their probability of default and, consequently, also their (potential state) bail-out.

Since we are able to demonstrate (in the next chapter) that this new mechanism reduces the probability of default and improves the stability of the bank, we suggest to use the periodically amount of ΔBOG for buying additional protection put options.

To conclude, our new mechanism is able to reduce the risk appetite, to equalize the distortion of competition caused by the de facto *BOG* (for too-big-to-fail banks) and to provide a recommendation of an alternative bank tax. This framework is funded by two different sources: a bonus reduction and additional funding cost. Nevertheless, the ´investment´ of these sources can not only significantly stabilize banks and consequently reduce potential public payments for bail-out, but also improves the expected firm value. Apart from lowering the probability of default, we will numerically show in the next chapter that the ´investment´ in the new mechanism is lower than the average increase in firm value.

---

[102] The "…" in equation (3.6) indicates that the calculation will be performed *T*-times, where *T* is the amount of periods of the observation period.

[103] To avoid back coupling effects with the price for the periodically bought protection put option, it is necessary to price the BOG only at the beginning.

3.4 Numerical Simulation of the Added Financial Stability

In the previous chapter, we mathematically elaborated a new mechanism and its theoretical impact on banks. In this chapter we focus on the numerical impact and provide results of this new mechanism.

3.4.1 The Simulation Method and Assumptions

We use Monte Carlo Simulation (and the software package Crystal Ball) to show how the new mechanism (i) increases the profit and financial stability of a bank, (ii) how it lowers the possibility (and, thus, social costs) of potential public bank bail-outs, and (iii) how it is optimal structured, i.e. which kind of put options optimize the outcome.

Steps and Iterations

In the simulation, the overall observation period is divided into 252 different steps. One can interpret the 252 steps as trading days and, thus, the overall observation period as one year. However, any other timeframe could be applied and delivers the same results. At each step the profit, the firm value, the default, etc. are calculated. The mechanism ends after the observation period. This allows us to measure the advantage of the new mechanism according to a financial year, which furthermore makes the implementation of this new mechanism in practice easier. We run the Monte Carlo Simulation with 10,000 iterations. This means that each of the 252 steps is calculated 10,000 times with different drift and volatility, as described in the section above.

Modelling the changes in profit

The increments ΔE_t of the equity value E_t and, thus, also the firm value V_t are determinated by the profit r_t. The profit r_t is the only externally given variable and follows the profitability of the financial sector. As the model is designed for any (and especially the extreme) situation in the financial sector, yearly mean μ_r and standard deviation σ_r of the profit r_t are simulated based on daily S&P Banking Index (BIX) returns over the period 2006 until

2011[104]. This time period ensures that we encounter a steep value decrease in an environment of high volatility. Hence, our simulation can be taken as a realistic extreme or stress test scenario. In other words, we are analysing our model within a framework of a financial crisis similar to the one of the years 2007-2009. However, in order to simulate different scenarios of profitability in the financial sector, the mean μ_r and the standard deviation σ_r are not constant across different Monte Carlo Simulations.

Contribution to the mechanism

First, we need to elaborate a percentage number indicating how much of a positive profit is skimmed by managers. Incorporating industry-wide average figures of a desired cost-income-ratio of *60%*, a split of personnel- and non-personnel-costs of *50%*, and thereof *50%* as variable personnel-costs, leads to a value for *b* of *40%*.[105]

Second, we are setting the bonus reduction parameter *h* to *25%*. This could be interpreted as a tax on the bonus payments used to stabilize the bank and, thus, to ensure future profits. However, it could be any other number, if politically possible.

Third, the funding cost paybacks are set to *f = 100%*. In other words, *100%* of the value of the received BOG has to be invested in the stability of the bank (i.e. invested in firm value). Concerning the level of the funding cost payback, the same holds true as for the bonus payments: it could be – if politically possible – any other number. The higher this percentage, the better for the soundness improvement of the bank.

These assumptions lead to a situation where the (average) costs of the mechanism are equally shared between bonus reduction and funding cost reduction, i.e. between managers and bank equity.

[104] Both the mean and the standard deviation are calculated based on the BIX by applying a rolling window of one year.

[105] According to the assumption in the text, the value b can be calculated as followes: b=[50% x 50% x 60%]/[1-60%]=38% which is rounded up to 40%.

3.4.2 Increasing Profit and Financial Stability to the Bank

As mathematically shown in the previous chapter, the new mechanism has a positive impact (a) on the increments of the firm value in the form of a higher mean and lower volatility and (b) on the financial stability. The following two sub-sections exhibit this impact numerically.

3.4.2.1 Improving the profit structure of the bank

Increase in the mean of the firm value

Since the protection put option (partly) hedges losses (negative profit), we expect that the simulated firm value increases compared to the situation without protection put. According to different environments, simulated with mean and deviation of the profit process, Figure 3.9 reveals the potential outcomes of the banks firm value V_t *without* and Figure 3.10 *with* the proposed mechanism. In Figure 3.9 the simulated mean of the firm value without the new mechanism is at *109.5* compared to *113.0* in case with the new mechanism, indicated in Figure 3.10. The red section (left to the mean firm value of *102.5* that refers to the outstanding debt (D_t)) indicates simulated cases of a bank default ($V_t < D_t$), whereas in the blue section (right to the mean firm value of *102.5*) the bank is solvent ($V_t < D_t$), which happens in *84.12%* of all simulated cases. In contrast, Figure 3.10 shows that with the new mechanism the probability of survival increases to *94.48%*.

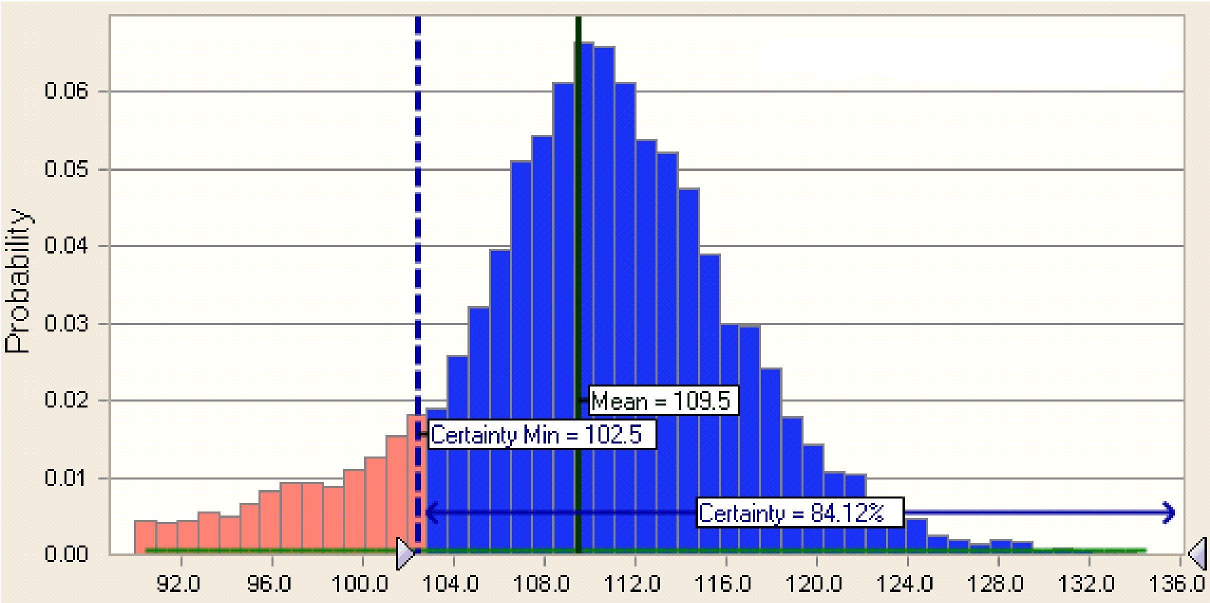


Figure 3.9: Firm value WITHOUT the new mechanism

The forecasted mean of the firm value <u>without</u> the new mechanism. The red section (left to the asset value of *102.5*) indicates cases of bank default ($V_t \leq D_t$) whereas in the blue section (right to the asset value of *102.5*) the bank survives ($V_t > D_t$). The survival probability is *84.12%*, whereas the probability of default amounts to *15.82%*.

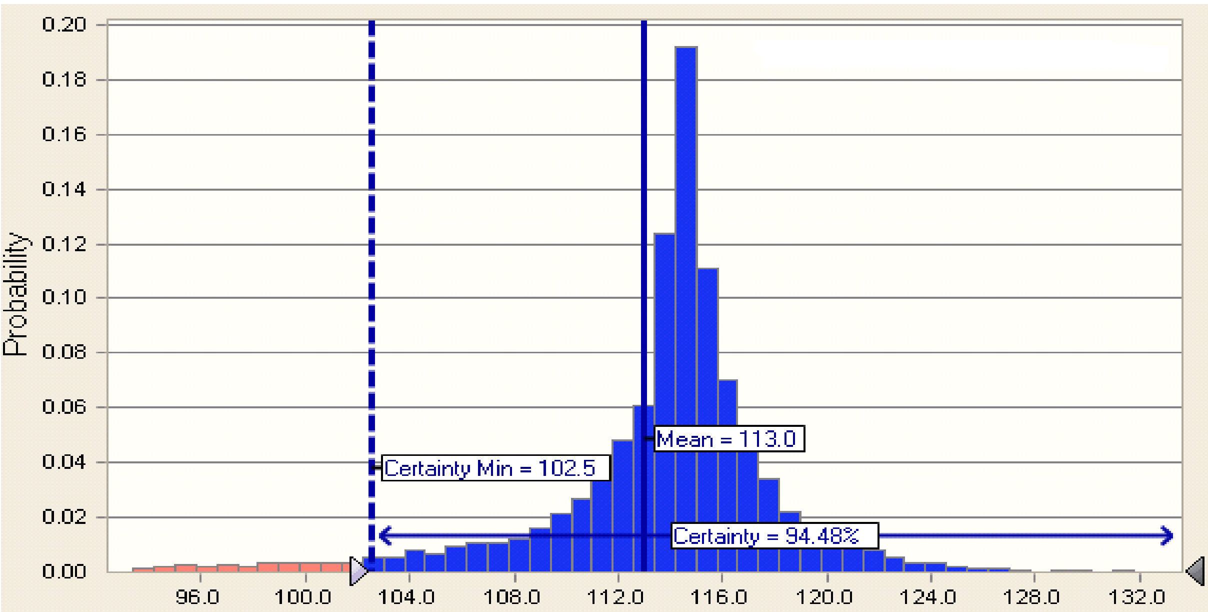


Figure 3.10: Firm value WITH the new mechanism

The red section (left to the asset value of *102.5*) indicates a default of the bank whereas in the blue section (right to the asset value of *102.5*) the bank survives. In *94.48%* of the simulated cases, the bank survives, which is around *10* percentage points higher than without the new mechanism.

Figure 3.11 presents firm value changes with and without the new mechanism (i.e., the difference between the firm value distribution in Figure 3.10 and those in Figures 3.9). In *82.66%* of all simulated cases, the new mechanism increases the profit of the bank (the blue section with positive profit). On the other hand, the red section (negative profit) refers to *17.34%* of all cases where the new mechanism is not paying off. The high value around and below zero refers to those cases where the protection put option is bought but is not needed (as the firm value process V_t is always larger than the debt process D_t). In these cases the new mechanism is more expensive than the situation without the mechanism as the price for the protection put has been paid and, thus, represents sunk costs to the bank´s P/L.

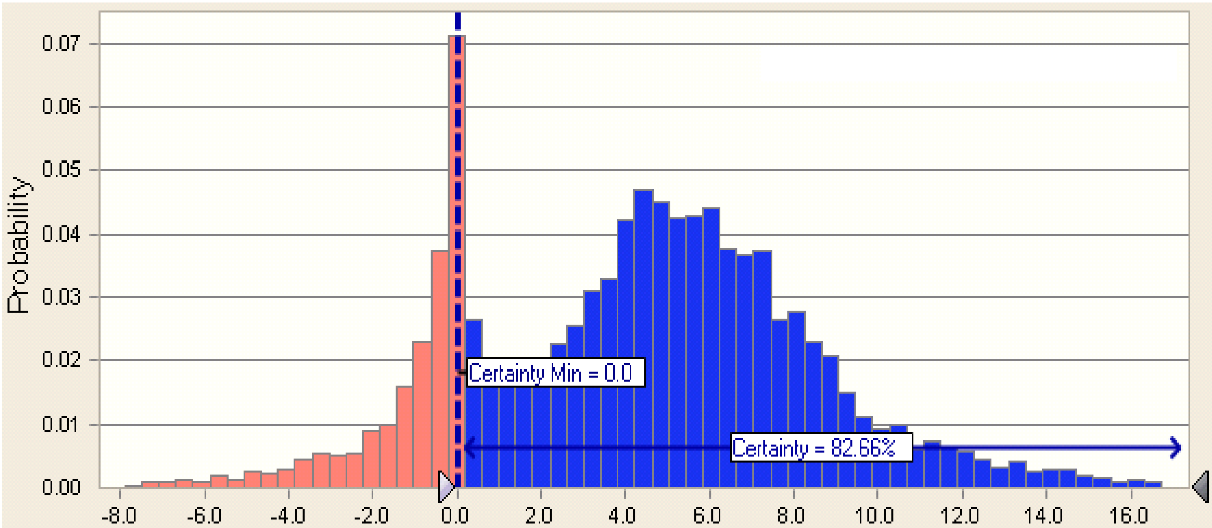


Figure 3.11: Difference of the firm value WITH and WITHOUT the new mechanism

Considering the Profit-advantage of the new mechanism including the reduction of bonus payments and funding paybacks, in *82.66%* of simulated cases is the asset value with the new mechanism higher than the asset value without the new mechanism. The relatively high value just below zero refers to cases where the knock-in-price has not been hit (i.e. where the distance to default is big enough not to cash-in the protection put option). In these cases the price for the put premium represents sunk costs.

Reduction in firm value volatility

As the new mechanism is designed to reduce the vega exposure of the profit process of managers, it is obvious, that the volatility of the firm value V_t decreases too. This volatility reduction is driven by changes in the stochastic process of equity capital E_t. Figure 3.12 exhibits this reduction in the volatility of V_t, with a mean of around *-18%*. The volatility decreases in more than *98%* of all cases.

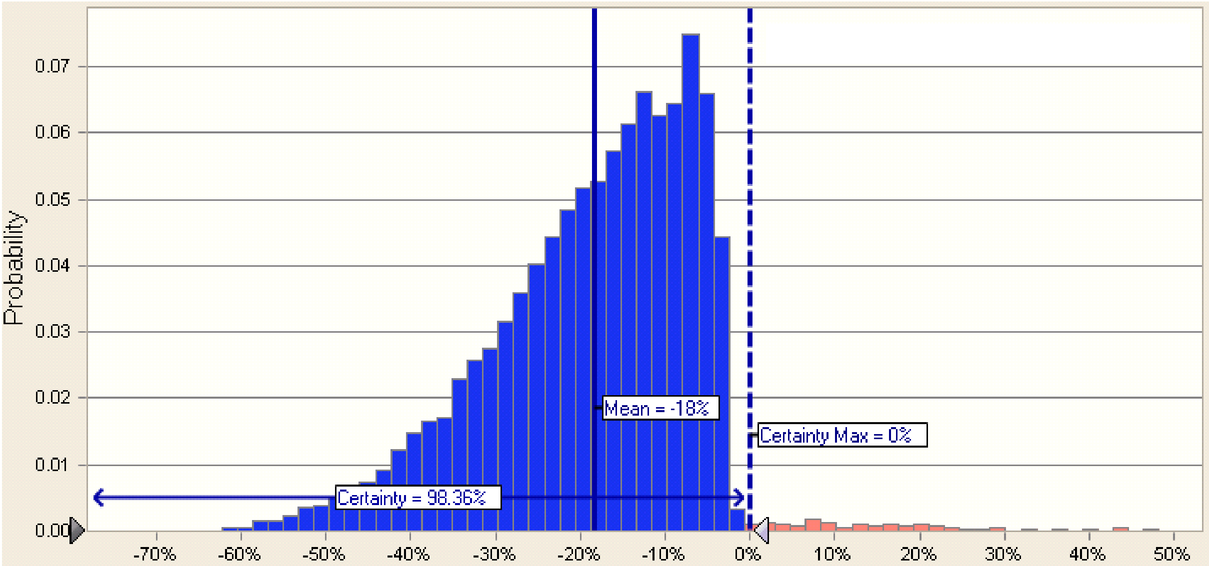


Figure 3.12: Decrease of firm value volatility caused by the new mechanism

This illustration shows the simulated difference of the firm value volatility WITH and WITHOUT the new mechanism. The simulated volatility reduction has its mean at *-18%*. Note that jumps of the asset value process are caused by the knock-in of the protection put. The barrier hit by the firm value process leads to an early cash-in of the protection put to avert the threatening default.

3.4.2.2 Enhanced Financial Stability

Measuring the soundness of a bank is not an easy task. Many ratios and measurements are designed to estimate the stability of its asset structure. We are using two common measures to investigate to what extent the mechanism can increase the soundness of banks. These measures are the simulated probability of default and the Z-Score.

Improvement of the probability of default

The probability of default is the most frequently used approach to measure the soundness and to rate the creditability. In our notation, a default occurs if V_t is smaller than D_t at any time in the observation period. As derived above this can be calculated with the Merton Model (1974) or can be simulated. Even though we use the idea of the Merton Model to describe the bank with stochastic processes for the debt- and equity-side, we regard this model as not applicable for measuring the advantages of our new mechanism. The reason for this is, that the protection put option, constantly bought over the whole observation period, increases in value if the bank is closer to default. These changes in the put option value (based on the firm value process V_t) cannot be captured by the Merton Model and, thus, the probability of default has to be estimated via Monte Carlo Simulation.

Using the new mechanism, a default occurs in *5.52%* of all cases, whereas in the case without the mechanism *15.82%* of all simulated firm value paths lead to bankruptcy. This is graphically shown in Figure 3.9 and Figure 3.10.

Improvement of the Z-Score

Beside the probability of default, the Z-Score[106] has become a common measure of the soundness of a bank. The popularity of this measurement in the banking industry stems from two facts: first, it is directly related to the insolvency definition of the Merton Model and, second, it is an adequate measure for all different types of banks as all banks face the same risk of running out of capital[107].

The Z-Score is defined as the equity E_t assets V_t ratio plus the (average) return on assets (ROA_t) divided by the standard deviation of the return on assets ($\sigma_{ROA\,t}$).

$$Z-Score = \frac{\frac{E_t}{V_t} + ROA_t}{\sigma_{ROAt}} \tag{3.7}$$

The Z-Score indicates the number of standard deviations the return has to fall in order to empty the equity capital. Note that the higher the Z-Score the more stable the bank is and the less likely a default occurs.

Based on the results gained in the previous chapter, where we have shown that we are able to reduce the asset value volatility, i.e., the volatility of the increments of E_t, and increase on the other hand the average change in E_t, it is obvious that the Z-Score increases if we apply the mechanism. Figure 3.13 shows the improvements of the Z-Score.

106 *See* Boyd and Runkle (1993).
107 *See* Cihak and Hesse (2007).

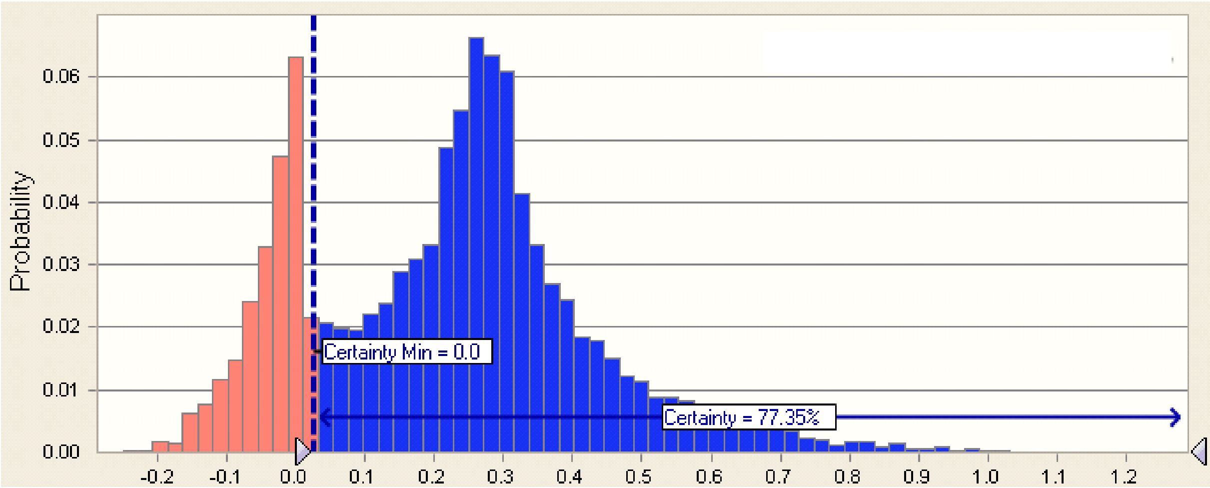


Figure 3.13: The improvement of the Z-Score based on the new mechanism

This Figure presents the differences between the simulated Z-Scores with and without the new mechanism. It shows that the Z-Score increases in *77.35%* of all cases and that the average improvement is about 0.25 Z-Score ratios.

It indicates the simulated absolute differences between the realized Z-Score *with* and *without* the new stabilizing mechanism. The peak around below the ordinate can be interpreted as simulated cases without default. The position of the peak some Z-Score-points below zero stems from the costs for the mechanism, as it does not pay off in case of no default (but only in 22.65% of all simulated cases).

3.4.3 Optimal Implementation of the Mechanism

Our new stabilizing mechanism is based on the idea to include the protection put option in the payoff profile of the bank. The best instrument for this mechanism is a down-and-in put option, that is only in the money with a given *strike price* if the underlying falls below a specific *knock-in-price*.[108] To optimize the structure of the protection put option, we analyse in a next step its optimal *strike price* and at which point, i.e., distance to default[109] (*knock-in-price*), the bank should start selling protection put options.[110] Both the strike price and the knock-in-price are indicated as percentage between 0% and 100%, where 0% represents the value of D_0, whereas 100% represents that of the starting firm value V_0.

[108] Note that the knock-in-price can be lower than the strike price.

[109] Distance to default refers in this notation to the distance between debt D_t and firm value V_t.

[110] Since the state is the issuer of the protection put option, banks need to cash-in the protection put option at the state.

Consequently, the stochastic process of the firm value with the proposed mechanism includes jumps where all cumulated protection put options are sold back to the state to push the firm value up and to save the bank from approaching default. A typical realization of the firm value process *with* and *without* the mechanism is illustrated in Figure 3.14.

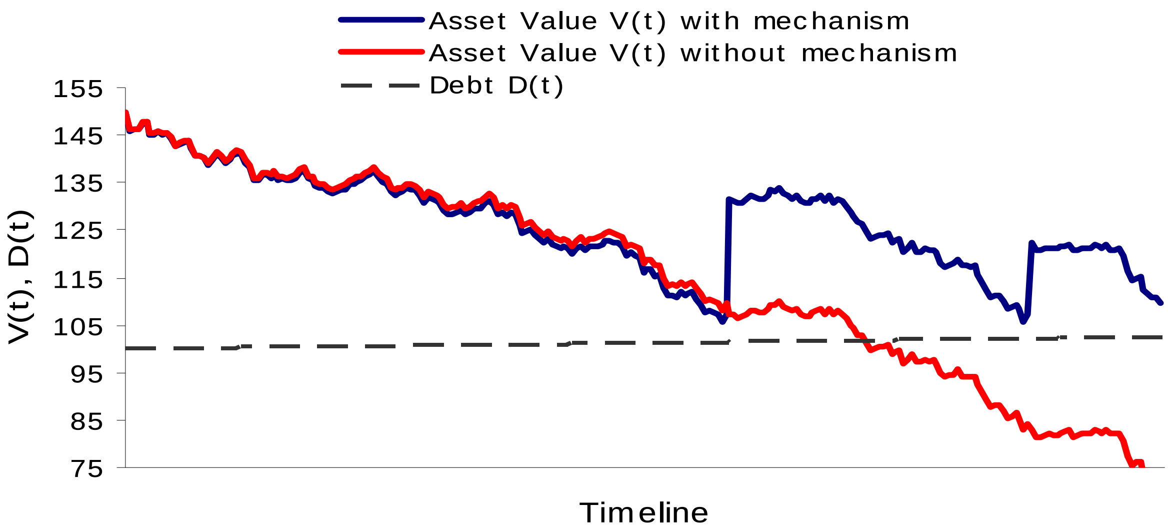


Figure 3.14: Illustrative firm value and debt process

Illustrative realization of the stochastic asset value process V_t (i) with and (ii) without the new mechanism, compared to the debt process D_t. If the asset value V_t falls below the debt process D_t, the bank is insolvent. The two jumps in the firm value process with the new mechanism, pushing the asset value process away from the zone of bankruptcy (i.e. below D_t), are caused by the previously bought protection put options.

The two jumps in firm value with the mechanism are caused by the sell of previously bought protection put options, which take place as soon as the firm value process V_t hits the knock-in-price of the put option. The banks contribution to the mechanism (i.e. the constantly bought put options) is visible as the process without the mechanism is (before the jumps) slightly higher than the process with the mechanism.

Using Monte Carlo simulation of this mechanism, we optimize the strike price and the knock-in-price[111] according to different objective functions: (i) the difference between starting and final firm value; (ii) the volatility reduction of the firm value; (iii) the simulated default-probability; and (iv) the Z-Score improvement. Across these four objective functions (i)-(iv), it turns out that the *optimal knock-in-price* is around *15%* between debt D_t and firm value V_t. The *optimal strike price* is around *50%* between debt D_t and firm value V_t.

[111] The optimization constraint for the strike price as well as for the knock-in-price is that is must be between 0% and 100%.

3.5 Summary

The financial crisis of the years 2007-2009 draws the attention of the financial world, regulators and academics to the practice of excessive risk taking by bank managers and the moral hazard created by bank bail-outs. Our objective is to create a new mechanism which could be implemented as bank tax alternative that (i) smoothens this risk taking, (ii) rebalances the moral hazard due to public bank bail-outs, and consequently (iii) enhances the stability of banks.

We study the incentives of managers of too-big-to-fail banks towards risk taking. Especially in such institutions, managers are not limited by creditors to take risks as creditors are holding a bail-out guarantee (*BOG*) from the state and, thus, have no incentives to control managers. We model the managers´ bonus payments as long call option on firm profit and the *BOG* as long put option on the firm value.

By implementing a new long protection put option in the banks payoff profile (sold by the state, and financed equally by managers and the bank as funding payback), we are able to enhance the expected profit, lower the volatility of the institution, improve their soundness ratios (probability of default and Z-Score), and, thus, reduce the risk of future governmental bail-outs. We consider the premium of this new protection put option as a bank tax alternative.

Our mechanism is a suggestion of how to structure a bank tax and how it should be used to enhance the stability of banks. Additionally, this new mechanism provides a tool for public authorities to navigate financial institutions through ups and downs or to actively diminish asset bubbles.

Chapter-Appendix: Proofs and Comments on the Implementation

I. Proof ad (i): higher expected return: In order to show the positive effect of the new mechanism on the expected return, we need to prove the inequality

$$E(\Delta E_t) > E\left(\Delta E_t{}^{wo}\right). \tag{3.1a}$$

Taking the expectation of equation (3.10) without the protection put option and incorporating the fact that the profit r_t is distributed as expressed in (3.1), we can calculate:

$$E\left(\Delta E_t^{wo}\right) = E\left(r_t - b \cdot Max(r_t, 0)\right) = \mu_r - b \cdot \Phi^{-1}(75\%) \cdot \sigma_r{}^2 \tag{3.2a}$$

Note that the factor $\Phi^{-1}(75\%)$ [112] in equation (3.2a) stems from the expected mean of the call option $Max(r_t, 0)$, whereas the operator $\Phi^{-1}(\,.\,)$ refers to the inverse cumulative standard normal distribution function.

The expectation in equation (3.5) with the protection put option, however, constitutes as follows:

$$E\left(\Delta E_t\right) = E\begin{bmatrix} r_t - b \cdot Max(r_t, 0) - \left(f_t \cdot \Delta BOG\right) \cdot P_t + \\ + \left(h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG\right) \cdot P_{t-1} \end{bmatrix} =$$

$$= E\left(\Delta E_t^{wo}\right) - \left(f_t \cdot \Delta BOG\right) \cdot E\left(P_t\right) + \left(h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG\right) \cdot E\left(P_{t-1}\right)$$

Focusing on our objective to prove that $E(\Delta E_t) > E\left(\Delta E_t{}^{wo}\right)$, we need to show that

$$\left(f_t \cdot \Delta BOG\right) \cdot E\left(P_t\right) \le \left(h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG\right) \cdot E\left(P_{t-1}\right)$$

[112] Since a call option is only in-the-money, when the profit r_t is positive, we only focus on the positive part of the density function of the profit. In order to ´divide´ the positive part of the density function, i.e. to calculate the mean, we need to calculate $\Phi^{-1}(75\%)$ which consequently yields the expected outcome of the call option.

Since P_t and P_{t-1} have approximately the same magnitude, they cancel out and we only need to focus on the factors:

$$f_t \cdot \Delta BOG \leq h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG$$

In case of a constant f_t over the observation time, this inequality holds true, which proves the increase of the expected return that comes along with the mechanism.

II. Proof ad (ii): lower volatility: In contrast to the expected return, the volatility of the firm value process is decreasing after the implementation of this stabilizing mechanism. This effect is driven by two reasons: (a) the shrinking incentives for managers to take risks, which influences directly the profit distribution $r_t \sim N(\mu_r, \sigma_r) \Rightarrow \bar{r}_t \sim N(\mu_r, \bar{\sigma}_r)$ with $\sigma_r > \bar{\sigma}_r$ and (b) the additional protection put option that smoothens the payoff function of ΔE_t even further. Thus, it is evident that

$$\sigma_r > \sigma_{\Delta E_t^{wo}} > \sigma_{\Delta E_t} . \tag{3.3a}$$

Even though the reduction of the volatility of the ΔE_t can be directly seen from the fact that the slope of the payoff-function of r_t and ΔE_t decreases by applying the new mechanism, it is possible to prove mathematically the amelioration of the volatility.

Due to the linearity of the expectation operator, we can split the calculation into the case of a positive r^+ and negative r^- return contribution. Furthermore, we apply the fact, that $\sigma_X{}^2 = E\left((X - E(X))^2\right) = E\left(X^2\right) - (EX)^2$.

$$\sigma_r{}^2 = \overbrace{E\left(-(\max(-r_t,0))^2\right)}^{r^-} + \overbrace{E\left((\max(r_t,0))^2\right)}^{r^+} - (E[r_t])^2$$

$$\sigma_{\Delta E_t^{wo}}{}^2 = \overbrace{E\left(-(\max(-r_t,0))^2\right)}^{r^-} + \overbrace{E\left((\max(r_t,0)\cdot(1-b))^2\right)}^{r^+} - \left(E\left[\Delta E_t^{wo}\right]\right)^2$$

$$\sigma_{\Delta E_t}{}^2 = \overbrace{E\left(-\left(\max(-r_t,0)\cdot(1-(h_{t-1}\cdot b + f_{t-1}\cdot\Delta BOG))^2\right)\right)}^{r^-} +$$

$$+\overbrace{E\left((\max(r_t,\,0)\cdot(1-b))^2\right)}^{r^+} - (E[\Delta E_t])^2$$

(Note that in $\sigma_{\Delta E_t}{}^2$ the cost for buying the protection for the next period, i.e., $(f_t \cdot \Delta BOG)$ is incorporated in the mean $(E[\Delta E_t])^2$, which can be seen in chapter 3.3.)

Showing that $\sigma_{\Delta E_t} < \sigma_{r_t}$, we take the difference between the two terms, apply the rule $E\left((a\cdot X)^2\right) = a^2 \cdot E\left(X^2\right)$ and use the symmetry[113] of the normally distributed r_t.

$$\sigma_r{}^2 - \sigma_{\Delta E_t^{wo}}{}^2 = \underbrace{\left[E\left[r_t\right] + b\cdot\Phi^{-1}(75\%)\cdot\sigma_r{}^2\right]}_{=E\left((\max(r_t,0))^2\right)} \cdot \underbrace{\left(2b-b^2\right)}_{\substack{>0\\ \text{since } b<1}} + \underbrace{\left(E\left[\Delta E_t^{wo}\right]\right)^2 - \left(E\left[r_t\right]\right)^2}_{>0} > 0 \qquad (3.4a)$$

Analogous, we can prove that

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113 Note that under the prerequisite of equation (3.2) that the return r_t is normally distributed, $E\left(-(\max(-r_t,0))^2\right)$ and $E\left((\max(r_t,0))^2\right)$ can be expressed as
$E\left((\max(r_t,0))^2\right) = E(r_t) + \Phi^{-1}(75\%)\cdot E(r_t - E(r_t))^2$ and $E\left(-(\max(-r_t,0))^2\right) = E(r_t) - \Phi^{-1}(25\%)\cdot E(r_t - E(r_t))^2$.

$$\sigma_{\Delta E_t^{wo}}{}^2 - \sigma_{\Delta E_t}{}^2 = \underbrace{\left[E\left[r_t\right] - b \cdot \Phi^{-1}(25\%) \cdot \sigma_r{}^2\right]}_{= E\left(-(\max(-r_t,0))^2\right)} \cdot$$

$$\cdot \underbrace{\left(2\left(h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG\right) - \left(\left(h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG\right)\right)^2\right)}_{>0 \ \text{since} \ (h_{t-1} \cdot b + f_{t-1} \cdot \Delta BOG) < 1} + \qquad (3.5a)$$

$$+ \underbrace{\left(E\left[\Delta E_t\right]\right)^2 - \left(E\left[\Delta E_t^{wo}\right]\right)^2}_{>0} > 0$$

As a consequence of (3.4a) and (3.5a) and due to transitive law, it is obvious that

$$\sigma_r{}^2 - \sigma_{\Delta E_t}{}^2 > 0 \qquad (3.6a)$$

Equations (3.4a), (3.5a), and (3.6a) verify the intuitive hypothesis from (3.3a) that the model lowers the volatility of the bank´s payoff and, thus, of its firm value process V_t.

III. Comments on the implementation of the new mechanism in practice: Financial markets and especially their participants are not the same all over the world. Therefore, a successful mechanism needs to be on the one hand homogeneous in order to treat all market participants equally but on the other hand flexible enough to respond immediately to a variety of different situations. In chapter 3, we elaborated our new mechanism with a – so far – small degree of freedom for regulators to adopt this framework to regional- and organizational-specific needs. Herewith, we extend our proposed framework to make it more flexible for regulators and, thus, more suitable to different market requirements.

So far, the bonus reduction parameter h is fixed and does not, e.g. depend on the path of the expected equity value increase $\mu_{\Delta E_t}$ (determinated by the profit (r_t)) or the equity value volatility $\sigma_{\Delta E_t}$ (determinated by the profit-volatility (σ_{r_t})). Of course, as the contribution of managers to the mechanism is a percentage of the previous return, they have to pay more in case the return is higher. Nevertheless, higher risk taking can further be penalized by changing the parameter h to a function $h(.)$.[114] For instance, this function could, e.g. be path-

[114] This function could be a continuous function or a discrete function that allows a (in finance regulation widely spread) corridor solution.

depend on the profit and profit-volatility of the last period(s) $h(\mu_{\Delta E_t}, \sigma_{\Delta E_t})$ or any other parameters.

A flexible bonus reduction function $h(.)$ has three positive effects:

(i) First, choosing a convex function[115] $h(.)$ could further punish excessive business expansion or business reduction. Both increase the organizational risk[116] and, consequently, could harm the stability of the whole economy.

(ii) Second, local regulators can use the function $h(.)$ to adapt the framework to regional and organizational needs.

(iii) Third, the flexibility of $h(.)$ could be used to apply this mechanism as tool to anti-cyclically stimulate or curtail the financial industry by changing the shape of the function. Compared to interest rate alterations[117], this instrument is not as ´blunt´ and allows regulators to more precisely target the appearance of asset bubbles.

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[115] To use this advantage, the function *h(.)* needs to be determined by the return and volatility of the last period(s).
[116] *See* Aussenegg, and Kronfellner (2011).
[117] *See* European Central Bank (2010), Lahard (2008), and Bruni (2009).

4 The Effect of Asset Liquidation on the (Bad Banks´) Stability

4.1 Introduction

The economy does not increase smoothly, but is a path of ups and downs, of bubbles and shocks, and of growth and crisis. In times of crisis, organizations think about their activities and where they can tighten their belts. As one can easily derive from the negative correlation of unemployment rate and GDP-growth, an economic downturn (such as the financial crisis) not only comes along with activity and (business-) portfolio restructurings, but also with reorganization and layoffs of employees. This reorganization has a deep impact on the company (microeconomic view) and the economy (job market: macroeconomic view) and might be, if not studied properly in advance, disruptive concerning their functionality.

These fundamentals of restructuring are applicable in any industry. Nevertheless, in this dissertation we (exemplarily) focus on the financial industry, since it is currently facing a period of severe restructuring. Many banks and organizations are dealing with restructuring and liquidation of (toxic[118]) assets and business segments. E.g., discussions with several banks have shown that their top management is currently discussing the problem of how to perform planned asset liquidation and, at the same time, organizational restructuring in the best and nevertheless most profitable way.

Thus, the following questions arise for banks (and any other organization) that have to sell a defined set of assets over a given period of time:

- *Which assets should be sold first in order to get the highest expected return of the liquidation? (Profit maximization)*

[118] Within and after the financial crisis, the financial world describes an asset to be toxic, if it (i) has fallen significantly in value and (ii) has provoked an increase in the risk weighted assets (RWA) and risk provisions due to rating-changes and increasing volatility. Credit derivatives are typical examples of toxic assets, like ABCPs (Asset Backed Commercial Papers), CDOs (Credit Debt Obligations), as well as other kinds of ABS-structures. Note that the notation ´asset´ always refers to a certain investment type such as the class of CDOs, ABCPs, toxic credits, etc. and not only to one specific share.

- *How can a bank prevent that not all involved employees/specialists leave the organization within a very short period of time during the restructuring process? (Minimizing the negative effects and risks of an organizational restructuring)*

Existing studies on asset liquidation and restructuring mainly deal with the consequences on the P&L statement through the execution of the assets itself. However, in bank reports one can easily see that especially labour costs are (in terms of yearly profits) also relevant and are, thus, underestimated in the current literature. Moreover, rating agencies that have to evaluate a restructuring plan or restructuring progress of a company, focus not only on the P&L statement and asset liquidation plans but also on the *organizational stability* within the restructuring process including human resource aspects.

Furthermore, Wilson (2009) has shown via the put-call-parity (considering the stockholders´ assets as a call and the creditors´ claims as a put option on the assets of the bank), that banks are rather reluctant to sell their toxic assets. According to the Merton Model (1974), options are more valuable when a banks´ assets are more volatile. As a consequence, Wilson has demonstrated that selling toxic assets reduces the volatility of banks´ assets and consequently decreases the value of the shareholders´ options. Thus, the buyer of toxic assets has to pay, in addition to the market price of the toxic assets also for the option price (as the price for the remaining options decreases by selling highly volatile toxic assets). Either shareholders are not willing to sell toxic assets when they do not receive any compensation for the loss in volatility or the buyers, mostly taxpayers, are overpaying, especially in an environment of high volatility.

However, lots of banks are forced by their stockholders as well as regulators (like FSA, SEC, or even the European Commission in the State Aid Process) to restructure toxic assets. Thus, such financial institutions need someone who is willing to purchase their (toxic) assets.

Asset liquidation as a field of research in financial mathematics emerged around the turn of the millennium and was triggered by the introduction of electronic trading systems[119]. The pioneers of this research area are Almgren and Chriss (1999) who developed the basis of many optimal execution algorithms by introducing an algorithm based on the efficient

[119] *See* Schoeneborn (2008).

frontier of an optimal execution.[120] Almost in parallel, Bertsimas, Hummelz, and Lo (1998) approached the problem of asset liquidation by applying the famous theory of dynamic programming and the Bellman Equation.[121] Based on these two pioneering papers, many authors adapted these concepts to different market situations, e.g. the price effect in illiquid markets (Pennesi and Darbha, 2009), the trade size, e.g., large block of securities (Ishii, 2009), small investors (Ishii and Honmachi, 2008), portfolio execution (Almgren and Chriss, 2000, Lorenz, 2008), and many more.

The contribution of this dissertation is, first, to model (to our best knowledge) for the first time the combination of (toxic) asset execution and the associated organizational restructuring, and second, to give banks a practical model to derive an effective and (compared to current best practice) more profitable restructuring.

In addition to the literature, we incorporate in the asset liquidation optimization problem: (i) The necessity of an organized staff reduction based on a 'smooth' organizational restructuring process for the sake of a high appreciation of *organizational stability*. (ii) The different characteristics of the two reasons for liquidation (cutback of toxic assets and well performing assets, such as compensatory measures[122] in the State Aid Process of the European Commission) and, thus, the distinction of different price dynamics. (iii) The link between asset market and labour market, expressed as probability to remain in the organisation. The more profitable a specific asset market the faster employees, specialized in this field, will find a new job. (iv) The current economic situation as well as the uncertainty of the future stock market development is modelled by using a Markov Switching approach for the stock price process.

By analyzing the combination of asset liquidation and organizational restructuring, we can show that within every restructuring process a significant asset reduction is always associated with a reduction of employees. By applying our new model, organizations are able to perform a restructuring process in a more efficient way in terms of profitability, risk and *organizational stability*.

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120 *See* Almgren and Chriss (1999).
121 *See* Bertsimas, Hummelz, and Lo (1998).
122 In a nutshell: Compensatory measures have to 'hurt' the bank benefiting from State Aid and to help its competitors.

The reminder of the chapter is organized as follows: Section 4.2 explains in more detail why it is currently necessary for banks - due to the financial crisis - to distinguish between the cutback of toxic assets and compensatory measures (required by states) and why the two asset types mostly appear together[123]. Furthermore, section two discusses the implementation of a liquidation of these two asset types for the organization. Section 4.3 presents the main model by explaining and developing every term of the overall target function, including different price processes for toxic and well-performing asset classes, incorporation of price impact functions, and the explicit modelling of *organizational stability*. Section 4.4 is devoted to specify a potential optimal liquidation strategy and to solve the target function elaborated in chapter three. Moreover, we compare the result with an industry best-practice-strategy of asset liquidation currently used by many banks. Section 4.5 provides results of the numerical solution to the elaborated model by using an example parameterized based on data from the banking industry. Finally, concluding remarks and suggestions for further research are set out in section 4.6.

4.2 Types of Asset Liquidation and its Implications on the Organization

As a consequence of the financial crisis, which we take as one example of an economic downturn, banks all over the world have to deal with the execution of their (toxic) assets and sometimes even have to ask for state aid to survive and to fulfill the capital-requirements in times of exploding risk weighted assets. Within the financial crisis, a total of $18 trillion has been spent by states in the form of direct capital injection, guarantees or asset purchases in order to restore the financial system[124]. This money has not been given to banks without any requirements. Especially the European State Aid Process is very strict and requires from banks a detailed restructuring plan.

123 However, even without a State Aid Process, a restructuring of toxic assets often contains also the restructuring (selling) of good assets (i.e., assets with a positive market performance), as market participants often restructure and refocus their business model. Thus, our model is valid for every asset restructuring and not only for those with compensatory measures.

124 *See* The Boston Consulting Group (2010).

4.2.1 Liquidation of Toxic Assets and Well-Performing Assets Compensatory Measures within the EU State Aid Process

Besides the liquidation of toxic assets, European banks are currently rethinking and redesigning their whole business models and even sell or shut down some – even well performing – business segments to be prepared for 'post-crisis-times'. In addition, especially banks with high exposures to toxic assets have to call for state aid due to increasing risk weighted assets in their toxic asset portfolios (in the form of capital injections) to keep an adequate capital-ratio (especially Tier-I capital). To avoid a distortion of competition or a moral hazard effect for risk taking, the European Commission only approves a state aid proposal of one of their member states if the corresponding banks in return abandon parts of their good-running-businesses and well-performing assets. The idea behind this requirement is to "hurt" banks with state aid and thus to help its competitors without state aid.[125] How many business segments or assets a bank has to quit can be stated by the bank itself (and approved by the member-state) in a viability report (for 'sound banks'[126]) or a restructuring plan (for 'non-sound banks'[127]).

It is important to distinguish between (i) liquidation of toxic assets, and (ii) liquidation of well-performing assets as compensatory measures. In other words, banks have to (due to compensatory measures) and want to (due to toxic assets) reduce a relatively large amount of assets. E.g., in the German and Austrian banking sector, some important players (especially the 'Landesbanken' in Germany as well as many Austrian banks) intended in their viability report or restructuring plan to diminish up to about 50% of their total assets within two to five years (compensatory measures and toxic asset liquidation combined). Since many European banks have already implemented such liquidation plans in their proposal for the European Commission or in their business plans, they have (as described in the introduction) to calculate the best way to execute what they already have signed. The development of an optimal way for this asset liquidation is the focus of this dissertation.

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125 But even in other sectors and apart from the European State Aid Process, organizations often abandon well-performing business segments and assets, for strategic- or risk-management reasons.

126 Soundness of a bank as legal term indicates whether the business model of the bank can be described as sound, i.e., healthy enough to last.

127 Within the state process a distressed bank is defined as non-sound if it has a business model that has generated a risk of insolvency.

4.2.2 Organizational Implication of Asset Reductions

The implications of a reduction of assets, due to compensatory measures and liquidation of toxic assets, on the employees behind the assets (traders, salesmen, researchers, as well as a proportion of administrative overhead employees, etc.) should not be neglected for the following reasons:

(i) Reducing staff has to come along with the reduction of assets to stay competitive and to keep industry-adequate ratios such as earnings per Full Time Equivalent (FTE), Cost-Income-Ratio, proportion of administrative overhead FTEs to total FTEs, etc.[128]
(ii) Besides potential losses through liquidation of toxic assets at a lower price than the purchase price, the reduction of staff has a positive effect on the total Profit and Loss (P&L) of a bank and thus has to be considered in any model.
(iii) Persistence of the staff is in the industry jargon also named *organizational stability*. Thus, the variance of staff costs is also an indicator for rating agencies and financial markets how stable the whole organisation is. A significant staff change ratio (i.e., above the normal fluctuation of around ± 10% p.a.[129]), is often interpreted with scepticism by the market since "organizational friction losses" are expensive in terms of time, money, and risk[130], and might even lead to bankruptcy as well (or at least increase the probability of a default).

4.3 The Model

This section defines the model and elaborates in more detail the different parts of the main equation that leads to the optimization problem in the next chapter. It describes the costs of the liquidation of assets (of toxic and well-performing assets[131]) and the impact of the corresponding staff reduction. Furthermore, it incorporates the effect of offering at once a significant package of the same securities on market prices.

[128] Based on such ratios rating agencies (e.g. Moody´s, S&P, or Fitch) calculate a bank's rating, which indicates the probability of bankruptcy, and, thus, is associated with credit spreads and also the cost of (needed) liquidity. For this reason, it is definitely important to constantly make sure to keep these ratios in a given range.

[129] This number is a rounded average of three big German banks.

[130] A restructuring always comes along with an increasing organizational risk, since know-how of the position and the organization itself might disappear along with the reduction of employees.

[131] In order to shorten the terms 'toxic assets and compensatory measures' (explained in section 2) we will just speak from now on of 'toxic and well-performing assets' instead.

4.3.1 Basic Model Environment

Consider a (bad) bank or a company seeking to sell a large block of $i \in \{1,\ldots, I\}$ different asset classes[132] over a fixed time interval $\{0,\ldots, T\}$ in N periods of the length $\tau = T / N$. Denote by $n_{t,i}$ the number of assets of class i sold in period t, with $t \in \{0,\ldots, T\}$, at the price $s_{t,i}$. We define the list $(X_0, \ldots, X_T)$ where each entry is an I-dimensional vector

$$X_t = \begin{pmatrix} x_{t,1} \\ \vdots \\ x_{t,i} \\ \vdots \\ x_{t,I} \end{pmatrix} \qquad \forall t \in \{0,\ldots,T\}$$

as a *trading strategy* such that each entry $(x_{t,i})$ defines the amount of assets that the bank plans to hold of I different asset classes at time t. $(S_0, \ldots, S_T)$ represents the vector of corresponding asset prices. The initial holding at $t = 0$ is set to $X_0 = X$ and after the liquidation at time T (for the latest) $X_T = 0$. Note that the increment of the trading strategy for asset class i

$$(x_{t,i} - x_{t-1,i}) = n_{t,i} \qquad \forall t \in \{0, \ldots, T\} \quad and \qquad \forall i \in \{1, \ldots, I\}$$

represents the trades in each period t such that

$$x_{t,i} = x_{0,i} + \sum_{z=1}^{t} n_{z,i} \qquad \forall i \in \{1, \ldots, I\}$$

Thus, at time t the current value of the whole (not yet executed) portfolio equals

$$\sum_{i=1}^{I} s_{t,i} \cdot x_{t,i}$$

[132] The notation ´asset classes´ refers not only to one specific share but to a group of the same type of assets such as the asset class of CDOs, the asset class of CDS, etc. For simplicity reasons we furtheron speak of ´assets´instead of ´asset classes´

4.3.2 Price Process

We differentiate between *j* toxic assets and *(I-j)* well-performing assets, with $j \in \{1,\ldots, I\}$. In other words, the bank is executing *j* different kinds of toxic assets and *(I-j)* well-performing (also called 'healthy') assets. Consequently, it is necessary to model the price process of the two types of assets differently. This implies that the *j* toxic assets follow different stochastic price processes:

$$s_{t,i} \quad \forall i \in \{1, \ldots, j\} =: s_{t,i \leq j}$$

than the *(I-j)* well-performing assets:

$$s_{t,i} \quad \forall i \in \{j+1, \ldots, I\} =: s_{t,i>j} \,.$$

(a) The **price process of well-performing assets $s_{t,i>j}$** can be modelled as a non-stationary stochastic process based on the two exogenous factors drift and volatility. The price process equals[133]:

$$s_{t,i>j} = s_{0,\, i>j} + \sum_{k=1}^{t} r_{k,i>j}$$

with increments (absolute[134] returns) of $\Delta s_{t,\, i>j} = s_{t,\, i>j} - s_{t-1,\, i>j} = r_{t,i>j}$, and

$$r_{t,\, i>j} \sim IID(\mu_{i>j}; \sigma^2_{i>j}). \qquad \forall t \in \{0, \ldots, T\}^{135}$$

133 Do keep this model as simple as possible we are not including other process features, like volatility clustering or fat tails.

134 We are using absolute instead of relative returns for model construction as we want to apply (in chapter 4) the Wald Equation to describe the current best practice, the Up&Out and Down&Out Strategy. Furthermore, this assumption is valid, as the initial values of all assets are standardized.

135 This is one of the most common and easiest *equation*s for a stock price process: a Random Walk with linear drift and a white noise process.

To keep things at this stage of the model as simple as possible, we assume a Random Walk, where the return for period *t* ($r_{t,i>j}$) only can take on two stages: an 'up step *u*' and a 'down step *d*':

$$r_{i,\,i>j} \sim \begin{cases} u \;\; with \;\; probability \;\; p_i \\ d \;\; with \;\; probability \;\; 1-p_i \end{cases}$$

Therefore we can easily derive for drift and volatility:

$$\begin{aligned} \mu_{i>j} &= E[r_{t,i>j} \,|\, \forall t \in \{0, \ldots, T\}] = p_i u + (1-p_i)d \\ \sigma^2_{i>j} &= Var[r_{t,i>j} \,|\, \forall t \in \{0, \ldots, T\}] = p_i(u-\mu)^2 + (1-p_i)(d-\mu)^2 = \\ &\qquad = p_i(1-p_i)^2(u-d)^2 + (1-p_i)p_i{}^2)(u-d)^2 = \\ &\qquad = p_i(1-p_i)(u-d)^2 \end{aligned}$$

This means for the price process in period *t*:

$$E[s_{t,i>j}] = t\mu_{i>j} = t(p_i u + (1-p_i)d) \tag{4.1}$$

$$Var[s_{t,i>j}] = t\sigma^2_{i>j} = tp_i(1-p_i)(u-d)^2 \tag{4.2}$$

Note that the drift of $t\mu_{i>j}$ makes the process non-stationary, which is necessary for a process that is supposed to describe changes in asset prices. Modelling with this simple Random Walk[136] allows us to establish a link between different parts of the *Net Liquidation Value* and also to perform a comparison with – in practice – often used up&out and down&out strategies.[137] The *Net Liquidation Value* describes the P&L of the whole restructuring procedure over the considered time interval T.

[136] One may criticise the assumption that the increments can just take two stages, but, however, with the Lindeberg-Levy Central Limit Theorem (CLT), one can easily show that this discrete process (the random walk) converges to a Brownian Motion as Δt converges to zero. This can be performed numerically by increasing the number of periods at a fixed total liquidation time T.

[137] The strategy is to sell an asset if the price exceeds or deceeds a fixed barrier.

(b) The **price process of toxic assets** $s_{t,i\leq j}$ is modelled, likewise, with drift and volatility, and in addition, incorporating that the drift can change within one step into three different states:[138]

$$s_{t,i\leq j} = s_{0,i\leq j} + \sum_{k=1}^{t} r_{k,i\leq j,(m_t)}$$

with

$$r_{t,i\leq j,(m_t)} \sim IID(\mu_{i,i\leq j\,(m_t)}; \sigma^2_{i,i\leq j}) \quad \forall t \in \{0, \dots, T\} \quad and \quad m_t = 1, 2, 3$$

and in our special case for simplicity:

$$r_{t,i\leq j,(m_t)} \sim \begin{cases} u \;\; with\;\; probability \;\; p_{i(m_t)} \\ d \;\; with\;\; probability \;\; 1 - p_{i(m_t)} \end{cases}$$

with the three different regimes $m_t = 1, 2, and\ 3$ for every toxic asset class $i \in \{1, \dots, j\}$.

This 'change in the regime' is especially used for describing cycles in economic growth[139], as well as business cycle asymmetry[140], and has been documented to be very useful to explain quick changes in stock market trends[141]. Thus, this Markov-Switching Model enhances the traditional price process models by a possible change into three regimes.

To model the future development of the price process of toxic assets, we are using three potential future economic scenarios for distressed (toxic) assets described by The Boston Consulting Group (2009): (i) V-shaped recession (brief downturn for 1 to 2 years, estimated probability: about 5%), (ii) U-shaped recession (long and deep downturn for 3 to 4 years with recovery, estimated probability: about 55%), and (iii) L-shaped recession (gradually recovery in 3 to 4 years but still recession, estimated probability: about 40%).

Thus, we need a three-regime Markov Switching Model as follows: Let $m_t=1, 2, 3$ be the state of the regime at time *t* such that

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138 These three states are in accordance to market estimates by the Boston Consulting Group (2009).

139 *See* Abberger and Nierhaus (2008).

140 *See* Hamilton (1989).

141 *See* Turner et al. (1990).

$$P[m_t = b \mid m_{t-1} = a] = P_{a,b}\,.$$

$P_{a,b}$ describes the probability for switching from regime *a* into regime *b*. Note that,

$$\sum_{i=1}^{3} P_{a,b} = 1 \quad \text{with} \;\; a = 1,\, 2,\, 3.$$

Since we have no information in which state the economy currently might be, we assume that it is in the middle regime (the U-shaped-recession), i.e. regime number 2 with drift $\mu_{i\leq j,(2)}$. According to discussions with world-wide operating banks over the last few months, the financial industry expects that the business with structured assets (which are currently called toxic assets) will either revive or shut down completely. In regime number 2 (steep decrease of the structured products business), the whole industry will follow which is modelled via a switch into another regime (either regime 1 or 3). Currently the whole finance industry is in a waiting position what might be the implications of the financial crisis to the industry such as (upcoming) regulatory changes.

Thus, we can model this fact by assuming $P_{a\neq b} = 0$ for for all *b* and for $a \neq 2$, *i.e.,* $P_{1;2} = P_{1;3} = P_{3;1} = P_{3;2} = 0$. In other words, if the market of toxic assets moves from the current regime 2 into another regime, it remains in this (new) position and does not switch back to another regime. According to the current economic description of The Boston Consulting Group (2009), the switches from the middle regime $(a = 2)$ are associated with the following probabilities $P_{2;1} = 5\%/T$, $P_{2;3} = 40\%/T$, *and* $P_{2;2} = (1 - P_{2;1} - P_{2;3}) = 1\text{-}45\%/T$, where *T* is the time of liquidation and, thus, corresponds to the numbers of the observed intervals in the model.

This change in the regime holds for all toxic assets $i \in \{1, \ldots, j\}$, i.e., the switching probability $P_{a,b}$ *with* $a, b = 1, 2, 3$ for the Markov Switching process is independent of asset *i*. Taking the advantage of modelling toxic assets as simple Random Walk plus a Markov Switching Process, $\mu_{i,(m_t)}$ and σ_i^2 are fully specified by p_i for up steps and $1\text{-}p_i$ for down steps by the equations:

$$E[s_{t,i\le j}] = t\mu_{i\le j} = t\sum_{m_t=1}^{3}\left[P_{2,m_t}(p_{i(m_t)}u + (1-p_{i(m_t)})d)\right] \tag{4.3}$$

$$\begin{aligned} Var[s_{t,i\le j}] = t\sigma^2_{i\le j} &= \frac{1}{2}\left\langle \begin{matrix} P_{2,1}\left[\left(t(p_{i(1)} - (1-p_{i(1)})(u-d)^2)^{1/2}\right) - E[s_{t,i\le j}]\right] + \\ P_{2,3}\left[E[s_{t,\le j}] - \left(t(p_{i(1)} - (1-p_{i(1)})(u-d)^2)^{1/2}\right)\right] \end{matrix} \right\rangle = \\ &= \frac{1}{2}\sum_{m_t=1,3} P_{2,b}\left|\underbrace{\left(t\sqrt{(p_{i(m_t)} - (1-p_{i(m_t)})(u-d)^2)}\right)}_{t\sigma_i} - E[s_{t,i\le j}]\right| \end{aligned} \tag{4.4}$$

Even though the mean and variance for each asset class in equations (4.3) and (4.4) is not as trivial as the respective equation for the well-performing asset classes in (4.1) and (4.2), for both types of asset classes (well-performing and toxic assets) we differentiate the I different asset classes in terms of drift and volatility. In other words, each asset class price process $s_{t,i}$ has different (but time invariant) drift μ_i and volatility σ_i^2 parameters as specification for $r_{t,i}$, the corresponding return.

For each p_i (and analogous for $p_{i(m_t)}$ $\forall m_t \in \{1, 2, 3\}$) and thus for each asset *i*, we assign the coefficient λ_i which can be interpreted as an indicator for the potential gains/losses of asset $i \in \{1, \ldots, I\}$:

$$\lambda_i(p_i) = 2(1-p_i) - 1 \;\; \forall i \in \{1, \ldots, I\} \tag{4.5}$$

Consider the boarder case of $p_i = 1$ (and thus $\lambda_i = -1$). This case means that with a probability of *1* the price process increases by up step *u*. Here the rational owner (e.g. a bank) of asset *i* is willing to keep the asset as long as possible to attain (with probability *p*) an *u* (up step) at each step. In contrary, if $p_i = 0$ then $\lambda_i = 1$, implying a downward movement (d) in each step.

Based on the definition of well-performing and toxic assets (and as the data will show in the next chapters), the probability of a positive return of a toxic asset (in any stage of the Markov Switching Process) is not greater than the probability of a positive return of a well-performing asset.

$$\forall m_t = 1, 2, 3: \ p_{i \le j,(m_t)} \le p_{i>j} \quad \text{with} \quad i, j \in \{1, \ldots, I\}$$

As will be demonstrated in chapter 3.5, λ_i is a link between the price process and organizational changes within the process of asset liquidation and organizational restructuring.

4.3.3 Price Impact

Since the supply and demand curve for almost all (even actively) traded securities are not perfectly elastic[142], each liquidation, especially if a significant package of the same asset class is sold, can affect the market price temporarily as well as permanently[143]. Economically spoken, this effect can be described as a temporary supply shock which changes the equilibrium stock price (given the same level of demand).[144] It has been shown that such temporary shocks lead to a (smaller) permanent effect, which remains at least until the end of the period of asset execution.[145] This impact can be described as a time-invariant (linear) function of the amount of assets traded, denoted as *h(.)* for the temporary and *g(.)* for the permanent price impact.

The influence on the price process by the price impact of trading n_t (buying/holding/selling the assets in period *t*) can be denoted as:

$$\hat{S}_t = S_t - h(n_t) - g(n_t)$$

The temporary price impact has no memory and is thus zero in the next period, i.e., a trade has just a temporary price impact in the period of the trade, but has no memory for the next trades in the same asset classes:

$$h(n^i_{\tilde{t}}) = 0 \quad \text{in period} \quad \tilde{t} \neq t, \quad \text{i.e.,} \quad Cov(\hat{S}_t; h(n_{\tilde{t}})) = 0 \ \ \forall \tilde{t} \neq t.$$

142 *See* Bertsimas and Lo (1998).
143 *See* Almgren and Neil (2000).
144 *See* Almgren and Neil (2000).
145 *See* Almgren and Neil (2000).

Since this price impact effect holds true for toxic as well as well-performing assets, we can apply the same function to all liquidation-holdings $s_{t,i}$ without any distinction between *j* toxic and *(I-j)* well-performing asset classes. The impact of the asset liquidation on the temporary and permanent price is schematically illustrated in Figure 4.1.

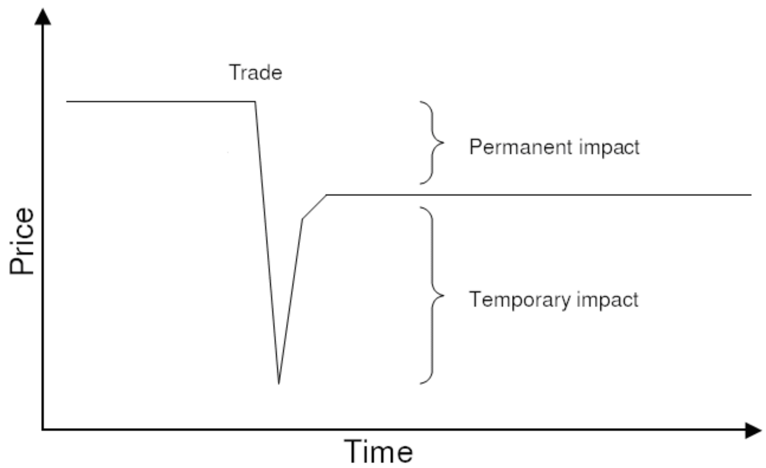

Figure 4.1: Illustrative explanation of the temporary and permanent price impact

The simplest case for the price impact function is a linear one (with *n* as variable and γ and η as slope), which also can be described as quadratic or exponential cost model[146]:

$$g(n) = \gamma n, \quad h(n) = \eta n$$

where γ and η are the slopes of the linear functions *g(.)* and *h(.)*.

In our approach, we use an exponential price function to model both the temporary and permanent price impact after asset liquidation. Using an exponential price function follows the belief that the more assets of a specific asset class one owns, the better this person knows the company and the more insider information this person might have.

[146] *See* Lorenz (2008).

4.3.4 Organizational Restructuring

Even though the aspect of organizational restructuring after a portfolio liquidation has a big influence on the balance sheet and the P&L of a bank, the organizational restructuring after a portfolio liquidation has not yet been discussed in the literature. One reason is that before the financial crisis the liquidation of assets normally did not mean to abandon a whole business segment and thus did not make the corresponding asset managers completely dispensable. Nowadays, and as a consequence of the financial crisis, many banks have committed themselves[147] not only to liquidate toxic as well as well-performing assets, but also to reduce their staff. Since banks do not need asset managers of the abandoned asset classes any more they resigns corresponding employees *after* (and not during) liquidation.[148] Under the assumption that each asset class is executed by exactly one full time employee (FTE), the completed liquidation of asset class *i* at time *t* (i.e., $x_{t,i} = 0$) is the starting point from where on the employer can resign the FTE, who is managing asset class *i*.

Consulting project experiences in the financial industry has shown that the elimination of the corresponding FTE from the payroll right after the liquidation is too inaccurate for any further modelling of the profit and loss statement, as employees remain (for some time) in the organisation even after the liquidation of 'their' asset class. Many (especially cost-cutting and banking merger) projects have proven empirically that the time between the decision of a termination (in our case the full liquidation of a certain asset class) and the cancellation of the FTE correspondent costs from the payroll, can normally last 0.5 to 1.5 years. This time lag is caused by two effects: First, the duration it takes to inform the employee of the termination (up to 6 months[149]) and second, the (especially in Europe expanded) legal period of notice (normally up to 1 year, depending on the working-contract).[150]

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147 This commitment can be abserved in a restructuring plan, submitted to the EU-Commission in the process of a State Aid Process or this commitment can be made towards its shareholders as a reaction to new developments after the financial crisis.

148 According to discussions with many European banks (esp. German "Landesbanken" and British Universal-Banks), it is common in the industry to resign the FTEs only after asset liquidation for 2 reasons: first, the liquidation has to be executed by someone who knows the portfolio and its market and second, to keep the employee motivated to execute the portfolio (for the bank) in the best way.

149 Duration to inform the employees includes the fact that these employees might still be needed for current projects etc.

150 These two time lag effects are developed with the HR- and Controlling-department of one of the biggest German banks within a consulting project to merge two banks. The figures are data-based estimations of these two departments.

(a) Description and Modelling of the Communication Density Function

We model the duration between the liquidation of asset *i* and the termination of the FTE dealing with asset classes *i* as equally distributed over the first 0.5 years[151] after liquidation with the following *density function*:

$$\hat{f}_i(x) = 2 \quad \forall x \in [0; 1/2] \;\Leftrightarrow\; \hat{f}_i(x) = 2 \cdot 1_{[0;1/2]}(x) \quad \forall x \quad (4.6)$$

The term $1_{[0;1/2]}(x)$ stands for the indicator function. Its value is 1 if x is element of the interval [0; 1/2] and 0 otherwise. Figure 4.2 illustrates graphically the density function of the duration between the end of asset class liquidation and the resignation of the corresponding employees.

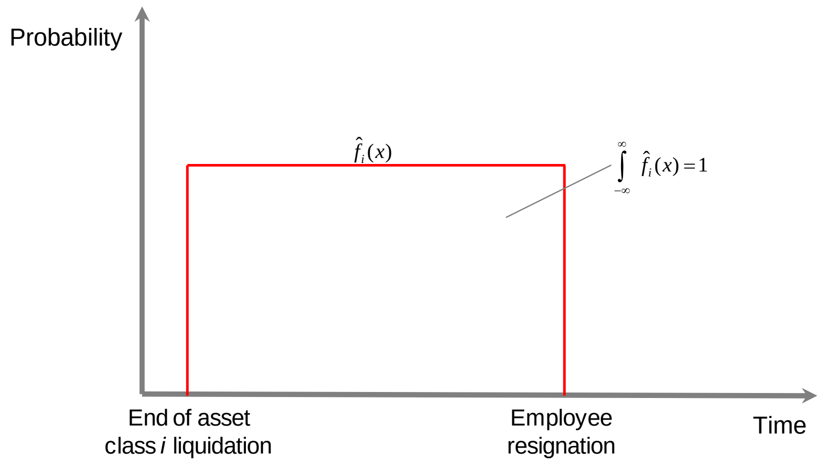

Figure 4.2: Communication density function – density function of the duration between asset liquidation and the resignation of the corresponding employee

(b) Description and Modelling of the Leave Density Function

If the labour market behind an asset classes is balanced, i.e., the resigned FTE can find a new job easily, the legal period of notice normally would not be exhausted completely by the employee. This can be expected for employees in charge of well-performing assets. However, the labour market for people trained in toxic assets might appear difficult. It is very likely that

[151] Note that any other duration can be applied in this model.

these people might exploit the full length of the period of notice (in our case assumed to be 0.5 years) to find a new job. We can model this period for employee *i* (managing asset class *i*) of staying in the company after liquidation of the correspondent asset class *i* as a *density function* $\tilde{f}_i$. This density function is determined by the labour market for jobs dealing with this specific asset class *i*. Economically spoken, the labour market is just a reflection of the industry's estimation of future profitability, i.e., expected return of the corresponding asset class in the future.

Therefore the density function $\tilde{f}_i$ is determined by λ_i, an asset-leave-linkage coefficient and given in the interval of 0 to 1 years.[152] In the following density function we link leaves of employees with the expected return of the corresponding asset class.

$$\tilde{f}_i(x, \lambda_i) = 2\lambda_i x + 1 - \lambda_i \tag{4.7}$$

Figure 4.3 illustrates this density function based on various coefficients λ_i. If λ_i is low (e.g. $\lambda_i = -1$) the employee leaves in a shorter period of time after asset liquidation. On the other hand, large values of λ_i (e.g. $\lambda_i = 1$) indicate that the employee leaves the company only after a larger period of time after asset liquidation. [153]

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[152] The model can be applied with any other time interval; however the result when to sell the assets is, consequently, slightly different.

[153] Note that the area under every density function in Figure 3 equals 1, i.e.:

$$\int_{-\infty}^{\infty} f_i(x, \lambda_i)dx = 1 \quad \forall \lambda \in [-1,1]$$

.

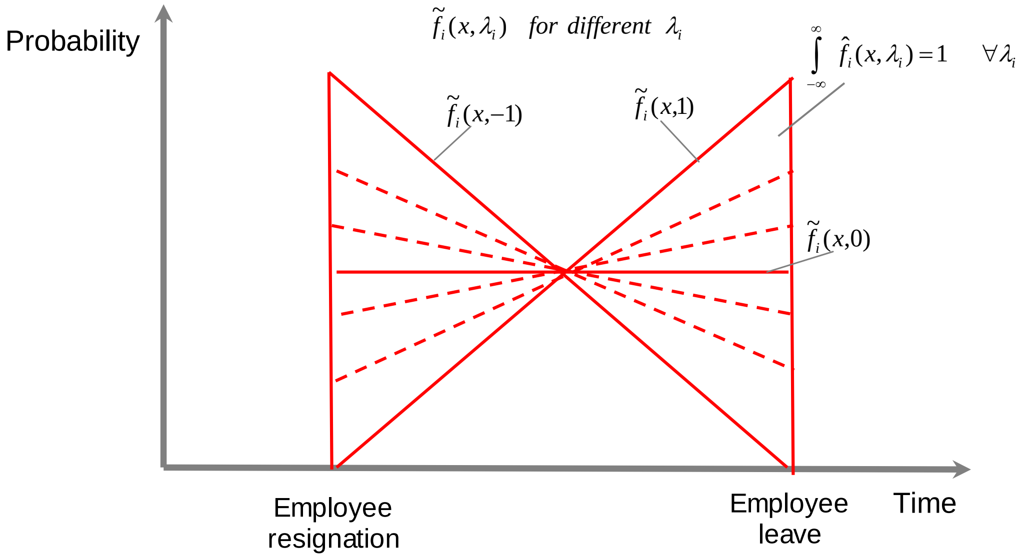

Figure 4.3: Leave density function – density function for one employee managing asset class *i* for staying in the company after asset liquidation

Note that $\tilde{f}_i$ (leave of employee after communication) will become relevant after the communication modelled in $\hat{f}_i$ occurs.

The mathematical **combination of both aspects** (first, applying the communication density function (a) and second, the leave density function (b)) of the organizational restructuring right after liquidation leads to a convolution ($\circ$) of the two density functions in (4.6) and (4.7). This leads the distribution of the time between the finalization of liquidation and the leave of the FTE:

$$f_i(x,\lambda_i) = \hat{f}_i(x) \circ \tilde{f}_i(x,\lambda_i) \tag{4.8}$$

with primitive function

$$F(t,\lambda_i) = \int_0^{1,5} f_i(x,\lambda_i)\,dx = 1 \quad \forall i \in I \tag{4.9}$$

where all parameters are taken from the separated density functions in (4.6) and (4.7).

Hence, the liquidation of assets does not only have a direct[154] effect on a bank‘s P&L but also an indirect effect due to less costs for employees (necessary to manage these asset classes). Beside these effects, it is crucial to eliminate the probability of a clustered leave of many employees. Given the specification above and as it will be shown in the numerical section later on, this can appear with a quite high probability. The reason is that well-performing assets will be sold more likely at the end of the liquidation period and employees are leaving quickly due to high λ_i [155]. On the other hand, toxic assets are sold earlier, but employees will stay longer in the company. For a certain overall liquidation period *T* this effect could generate a cluster of leaves. This cluster can be accessed in quarterly reports, declared in the profit and loss statement. They are typically interpreted by the financial industry (such as counterparties and rating agencies) as organizational instability, including organizational risk. The top management of banks are well aware of this problem, but would need a framework to deal with it properly, ideally in a mathematically optimal way.

4.3.5 Target Function and Constraints

Finally, we have to combine the elaborated effects and terms from above into one target function that has to be optimized. We define the *Net Liquidation Value G* of all initial holdings S_0X_0 as a function of the *trading strategy* n_t. In other words, one can maximize the *Net Liquidation Value* of assets by finding the optimal *trading strategy* n_t. The *Net Liquidation Value* is defined as:

$$G = \sum_{t=0}^{T} \sum_{i=1}^{I} \left[n_{t,i} \hat{S}_{t,i}(n_{t,i}) - c_i \left(1 - F(\delta_{t,i}, \lambda_i)\right) \right] \tag{4.10}$$

where $\hat{S}_{t,i}$ is the price of asset class *i* minus the temporary and permanent price impact:

$$\hat{S}_{t,i} = S_{t,i} - h(n_{t,i}) - g(n_{t,i}) .$$

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[154] If the book value is below the faire value, the liquidation of the toxic assets causes a loss. Otherwise, the liquidation has a positive effect on the balance sheet.
[155] Mathematically described as a higher expected return.

Furthermore, c_i represents the wage and additional costs of the employee managing asset class i. δ_i indicates the time where all holdings of asset class i have been sold such that in each period $\delta_i = 1$, i.e., $x_{t,i} = 0 \quad \forall t \geq \tilde{t}$. $\tilde{t}$ is the time, where all assets are sold which is by definition the starting point from where on the banks start to resign the corresponding FTE. And $\delta_i = 0$ when $x_{t,i} \neq 0 \ \forall t < \tilde{t}$.

$$\delta_{t,i}(x_{t,i}) = \left| sign(x_{t,i}) - 1 \right| \tag{4.11}$$

This additional equation is just a mathematically needed relation to make equation (4.10) work. It simply stops the selling process in the algorithm.

Obviously, a rational bank wants to maximize this *Net Liquidation Value G* to obtain as much as possible from the planned asset liquidation (first term in equation 12) and organizational turnover (second term in equation 12):

$$\hat{G} = \underset{(n_{t,i})}{Max} \sum_{t=0}^{T} \sum_{i=1}^{I} \left[n_{t,i} \hat{S}_{t,i}(n_{t,i}) - c_i \left(1 - F(\delta_{t,i}, \lambda_i)\right) \right] \tag{4.12}$$

By using the telescoping sum in equation (4.12), it can be re-written as:

$$\hat{G} = \underset{(n_{t,i})}{Max} \sum_{i=1}^{I} \left\langle \underbrace{x_{T,i} \hat{S}_{T,i}(n_{T,i})}_{=0} - \sum_{t=2}^{T} \left[x_{t-1,i} \underbrace{\left(\hat{S}_{t,i} - \hat{S}_{t-1,i} \right)}_{:= \Delta \hat{S}_{t-1,i}} \right] - \underbrace{x_{0,i} \hat{S}_{1,i}}_{\substack{not \\ relevant \\ for\ Max}} - \left[c_i \left(1 - F(\delta_{t,i}, \lambda_i)\right) \right] \right\rangle$$

and thus can be transformed into a minimization problem:

$$\hat{G} = \underset{(n_{t,i})}{Min} \sum_{i=1}^{I} \left\langle \sum_{t=1}^{T} \left[x_{t,i} \Delta \hat{S}_{t,i} \right] + \left[c_i \left(1 - F(\delta_{t,i}, \lambda_i)\right) \right] \right\rangle \tag{4.13}$$

Since we consider the case where the bank does not only want to maximize the estimated *Net Liquidation Value* $E(\hat{G})$ but also the *organizational stability*, we focus on the second moment of

$\hat{G}$. Note that the second moment, the variance, can be seen as an indicator for changes of $\hat{G}$ and its minimization leads to an increase of stability.

Consequently, the optimization problem in (4.13) will be adjusted by a term that measures the stability. Therefore we define a utility function $U(a,b,\hat{G})$ where the parameter *a* denotes the weight for asset-stability and *b* the weight for organizational-stability. These two parameters, *a* and *b*, indicate the importance of asset- and *organizational stability* to the applier of the model and are defined to be between *0* and *1*. The utility function is defined as:

$$U(a,b,\hat{G}) = \underset{(n_{t,i})}{Min}\left(E(G) + V(a,b,G)\right) \tag{4.14}$$

where *V(.)* represents the non-centered second moment of *G*, the *Net Liquidation Value* in (4.13), weighted by the parameters *a* and *b*:

$$V[a,b,G] = \left\langle \sum_{i=1}^{I} \left\langle \sum_{t=1}^{T} \left[a \cdot \left[x_{t,i} \Delta S_{t,i} \right] + b \cdot \left[c_i \left(1 - F(\delta_i, \lambda_i)\right)\right]\right]^2 \right\rangle\right\rangle \tag{4.15}$$

In a next step we derive the mathematical solution of the *trading strategy* n_t in the optimization problem $U(a,b,G)$. In order to calculate the first and second moment of the *Net Liquidation Value* in (4.13), we have to decompose *G* into three parts: two for the asset sale (of toxic and well-performing assets) and one for *organizational stability*:

$$G = \underbrace{\sum_{i=1}^{I}\sum_{t=1}^{T}\left[x_{t,i}\Delta\hat{S}_{t,i}\right]}_{\substack{G_{sale,i\leq j} \\ (Toxic\ Assets)}} + \underbrace{\sum_{i=1}^{I}\sum_{t=1}^{T}\left[x_{t,i}\Delta\hat{S}_{t,i}\right]}_{\substack{G_{sale,i>j} \\ (Well-\text{performing}\ Assets)}} + \underbrace{\sum_{i=1}^{I}\sum_{t=1}^{T}\left[c_i\left(1-F(\delta_{t,i},\lambda_i)\right)\right]}_{\substack{G_{FTE} \\ (Organizational\ Stability)}} \tag{4.16}$$

Thus, also the expected *Net Liquidation Value* consists of three components:

$$E[G] = E[G_{Sale,i\le j}] + E[G_{Sale,i>j}] + E[G_{FTE}] = \sum_{i=1}^{j}\sum_{t=0}^{T} x_{t,i}\left(E[s_{t,i}] - g(x_{t,i}) - h(x_{t,i})\right) + \\ + \sum_{i=j+1}^{I}\sum_{t=0}^{T} x_{t,i}\left(E[s_{t,i}] - g(x_{t,i}) - h(x_{t,i})\right) + \\ + \sum_{i=1}^{I} c_i\left[\left(\sum_{t=0}^{T}\left|\delta_{t,i} - 1\right|\right) + F_{\lambda_i}^{-1}(0{,}5)\right] \tag{4.17}$$

And under the (– in our opinion – realistic) assumption that the correlation between the price increments of well-performing and toxic assets equals zero we receive the second moment of the utility function *U* in (4.14):

$$V[a,b,G] = a_{i\le j}^2 V[G_{Sale,i\le j}] + a_{i>j}^2 V[G_{Sale,i>j}] + b^2 V[G_{FTE}] + \\ + 2a_{i\le j} b Cov[G_{Sale,i\le j}; G_{FTE}] + 2a_{i>j} b Cov[G_{Sale,i>j}; G_{FTE}] = \\ = a_{i\le j}^2 t\sigma_{i\le j}^2 + a_{i>j}^2 t\sigma_{i>j}^2 + b^2 \sum_{i=0}^{I}\sum_{t=1}^{T}\left\langle \left[c_i\left(1 - F(\delta_{t,i}, \lambda_i)\right)\right]^2 \right\rangle + \\ + 2a_{i\le j} b Cov[G_{Sale,i\le j}; G_{FTE}] + 2a_{i>j} b Cov[G_{Sale,i>j}; G_{FTE}] \tag{4.18}$$

The aim is now to maximize the expected profit of asset liquidation, consisting of a Sales- and an FTE-component (see (4.17)). In contrast, the object of *organizational stability* (represented in the FTE-component) only is to minimize its variance. The variance of the Sales-component, however, is not relevant, as assets are only bought, sold, and held to maximize the profit and the changes of this processes do not directly alter the *organizational stability*. The indirect impact of asset changes (i.e., the leaves of FTEs after asset liquidation) is integrated in $b^2 V[G_{FTE}]$ in (4.18). Thus, we can assume that the parameter for asset-stability $a = 0$, which reduces $V[a,b,G]$ to:

$$V[a,b,G] = b^2 V[G_{FTE}] = b^2 \sum_{i=0}^{I}\sum_{t=1}^{T}\left\langle \left[c_i\left(1 - F(\delta_{t,i}, \lambda_i)\right)\right]^2 \right\rangle \tag{4.19}$$

Note that, by setting $a = 0$, we neglect all other parts of the variance expressed in (4.18) since only the variance of the FTEs is directly influenceable and relevant for *organizational stability*. Therefore, the optimization problem can be written as:

$$U\left(b,\hat{G}\right)=\underset{(n_{t,i})}{Min}\left(\underbrace{E(G)}_{\substack{Net\\Liquiditation\\Value}}+\overbrace{b^2V[G_{FTE}]}^{\substack{Organizational\\Stability}}\right) \tag{4.20}$$

4.4 The Optimal Trading Strategy

Before we derive a mathematical solution for the target function $U(b,G)$ of the optimization problem in (4.20), we calculate the *Net Liquidation Value* of another possible liquidation strategy, which is currently best practice in the market: the Up&Out and Down&Out strategy to liquidate assets.

4.4.1 Trivial Up&Out and Down&Out Strategy as Best Practice

Facing a planned restructuring of assets, banks currently often define an *upper price barrier* $\overline{Z}_i$ and a *lower price barrier* $\underline{Z}_i$ for each Asset i. Assets are sold above $\overline{Z}_i$ and below $\underline{Z}_i$ if the asset price $s_{i,t}$ of asset *i* hits either the upper $\overline{Z}_i$ or the lower barrier $\underline{Z}_i$. We assume (as it can be very often seen in practice) that the bank sells the whole asset class such that in the next period $x_{i,t+1}=0$.

For the special case of a trivial price process[156] with $P[r_{t,i}=1]=p_i$ and $P[r_{t,i}=-1]=1-p_i \ \forall i\in\{1,\ldots,I\}\ \forall t\in\{0,\ldots,T\}$, where $r_{t,i}$ is the return of asset *i* in period *t*, it can be shown applying the Wald-Equation[157] that the process hits a given barrier, i.e., $s_t=Z$, at the average time t_Z with:

$$E[\bar{t}_Z]=\frac{\overline{Z}}{2p-1} \quad \text{for} \quad p>1/2 \quad \text{and} \quad E[\underline{t}_Z]=\frac{\underline{Z}}{2(1-p)-1} \quad \text{for} \quad p\leq 1/2.$$

[156] In order to use the Wald Equation a trivial price process (i.e. up step with 1 und down step with -1) is essential.
[157] *See* Ross (1996) and its application to asset price time series in Kronfellner (2008).

For the *i* (different) **well-performing asset classes**, denoted as $i > j$, one can easily calculate the expected time $\bar{t}_{Z_{i>j}}$ where $\overline{Z}_k \ \forall k > j$ is the upper barrier that has to be hit:

$$E\left[\bar{t}_{Z_k}\right] = \frac{\overline{Z}_k}{2p_k - 1}.$$

Since for the well-performing assets the probability *p* of a positive return in the next time period is – per definition – always greater than 0.5 (i.e. assuming a positive expected return), we can (nearly) disregard the lower barrier, as a hit of the well-performing assets on the lower barrier is very unlikely[158]. The expected *Net Liquidation Value* $E(\hat{G})$ for well-performing assets, i.e., for *i* assets with $i > j$, is therefore:

$$E(\hat{G}_{i>j}) = \sum_{k=j+1}^{I} \left[x_0^k \overline{Z}_k \left(h(x_0^k) - c^k (t_{Z_k} + F_{\lambda_k}^{-1}(0.5))\right)\right] \tag{4.21}$$

To express the *Net Liquidation Value* for **toxic assets**, denoted as $i \leq j$, it is necessary to incorporate the Markov Switching process defined in chapter 3.

$$\begin{aligned} E(\hat{G}_{i\leq j}) = & \sum_{k=1}^{j} P_{2,1} \left[x_0^k \overline{Z}_k \left(h(x_0^k) - c^k (\bar{t}_{Z_k} + F_{\lambda_k}^{-1}(0.5))\right)\right] \\ & + P_{2,3}\left[x_0^k \underline{Z}_k \left(h(x_0^k) - c^k (\underline{t}_{Z_k} + F_{\lambda_k}^{-1}(0.5))\right)\right] + \\ & + (1 - P_{2,1} - P_{2,3})\left[x_0^k \underline{Z}_k \left(h(x_0^k) - c^k (t_{\underline{Z}_k} + F_{\lambda_k}^{-1}(0.5))\right)\right] = \\ = & \sum_{k=1}^{j} \sum_{m_t=1}^{3} P_{2,m_t} \left[x_0^k \overline{Z}_k \left(h(x_0^k) - c^k (\bar{t}_{Z_k} + F_{\lambda_k}^{-1}(0.5))\right)\right] \end{aligned} \tag{4.22}$$

Due to the additivity of *E* it follows: $E(\hat{G}) = E(\hat{G}_{i\leq j}) + E(\hat{G}_{i>j})$

Chapter 4.5 numerically compares this trivial liquidation strategy with our new model developed in chapter 4.3.

158 Note that the probability of a barrier hit also depends on the volatility of the price process.

4.4.2 Definition of the Optimization Problem

To solve the optimization problem in (4.20) it is in a first step necessary to divide equation (4.20) into two separated terms, $E[G]$ and $V[G_{FTE}]$, to make it more comprehensive.[159] When we just look at $E(G)$, the *Net Liquidation Value*, it is obvious that the optimal trajectory must be to sell all assets with a positive mean return in the price process at the end of the liquidation period (t = *T*) and to sell all assets with negative mean return at the beginning of the liquidation period (t = 1).[160] Remember that the expected mean return (i.e., the absolute increments of the price process) is given by the probability p_i for well-performing assets (with $i > j$) and $p_{i(m_t)}\ \forall m_t \in \{1, 2, 3\}$ for toxic assets (with $i \leq j$) for 'up steps' and $1 - p_i$ and $1 - p_{i(m_t)}$ for 'down steps' for each asset *i*. Thus, for well-performing asset *i*:

$$\mu_{t,i>j} = E[r_{t,i>j} \mid \forall i \in \{j+1, \ldots, I\}\ \forall t \in \{0, \ldots, T\}] = p_i u + (1 - p_i) d \quad \text{with i > j,}$$

and for toxic assets *i*:

$$\mu_{t,i \leq j} = E[r_{t,i \leq j} \mid \forall i \in \{1, \ldots, j\}\ \forall t \in \{0, \ldots, T\}] = \sum_{m_t=1}^{3} \left[P_{2,m_t} \left(p_{i(m_t)} u + (1 - p_{i(m_t)}) d \right) \right] \quad \text{with } i \leq j.$$

However, even for positive mean μ of the price process, we still have to incorporate that the bank has to pay also for the employees managing the specific asset class. As a consequence, we have to incorporate this additional costs and have to separate all assets again, since the performance of an asset with a slightly positive mean can become negative when incorporating labour costs c_i of the corresponding employees, expressed in:

$$[\mu_i x_i - c_i] \quad = \quad \begin{cases} < 0 \ \ start\ \ selling\ at\, t = 0\ \ and\ \ finish\, at\, t_i^{0\rightarrow} \\ > 0 \ \ start\ \ selling\ at\, t = T - t_i^{\leftarrow T}\ and\ \ finish\, at\, T \end{cases}$$

---

159 Note, however, that within the optimization problem, the two terms can not be regarded as separated, since they interfere with each other.

160 For toxic assets it is crucial to incorporate the (above specified) Markov-Switching approach in order not to neglect the possibility that the expected return of these assets can (potentially) become positive.

This divides all assets into two groups: Those which have to be ideally sold at the end of the liquidation period and those that have to be sold at the beginning. In general, and as already mentioned previously, one could say that the group of assets sold at the end are mostly well-performing assets, since it is better for the bank to benefit from a positive price process for more periods. On the other hand, toxic assets should be sold at the beginning. It can be shown, that with no more specifications the optimal trajectory of the *Net Liquidation Value* $E(G)$ would be to set $t_i^{0\rightarrow}$ to *1* (i.e., selling between t = 0 and t = 1) and $t_i^{\leftarrow T}$ to *T-1* (i.e., selling between t = T-1 and T). In other words: to sell one group in the first period completely and the other group in the last period.

Yet, the optimal trajectory of $U\left(b, \hat{G}\right)$, expressed by the trading strategy $n_{t,i}$, is a function of when to stop selling assets with an overall negative return ($t_i^{0\rightarrow}$) and when to start selling assets with an overall positive expected return ($t_i^{\leftarrow T}$). It furthermore depends on: First, the importance of the *organizational stability*[161] expressed by parameter *b*, second, the duration of the overall liquidation *T*, and third, the probability p_i of an 'up step' for asset *i*. At this stage, given these three parameters, we already can assume that the optimal liquidation with a focus on *organizational stability* should be more "smoothed" than just setting $t_i^{0\rightarrow}$ to *1* and $t_i^{\leftarrow T}$ to *T-1*, i.e. selling non-performing (toxic) assets immediately and selling well-performing assets at the end of the liquidation period.

Mathematically spoken, we can distinguish between two types of density functions for $t_i^{0\rightarrow}$ (i.e., when to stop selling assets with an overall negative expected return) and $t_i^{\leftarrow T}$ (i.e., when to start selling assets with an overall positive expected return) that explain the speed of the sale for toxic and well-performing assets. We derive the density functions:

toxic assts:
$$f_i^{0\rightarrow}(x, t_i^{0\rightarrow}) = MAX\left[-2\frac{1}{(t_i^{0\rightarrow})^2}x + \frac{2}{t_i^{0\rightarrow}}\ ;\ 0\right] \tag{4.23}$$

[161] As the *Net Liquidation Value* is expressed in currency units, also the organizational persistence has to be expressed in currency units (i.e., numbers of FTE multiplied by their costs (salaries) c_i).

well-performing assets: $$f_i^{\leftarrow T}(x,t_i^{\leftarrow T}) = MAX\left[\frac{2}{(t_i^{\leftarrow T})^2}x - \frac{2}{(t_i^{\leftarrow T})^2}T + \frac{2}{t_i^{\leftarrow T}}\ ;\ 0\right] \quad (4.24)$$

Both functions assure the necessary condition for the density functions:

$$\int_0^T f_i^{0\rightarrow}(x,t_i^{0\rightarrow})dx = \int_0^T f_i^{\leftarrow T}(x,t_i^{\leftarrow T})dx = 1 \quad \forall t_i^{0\rightarrow} \wedge t_i^{\leftarrow T} \in (0;T)$$

The difference between the two destiny functions, one for toxic assets (4.23) and one for the well-performing assets (4.24), can be graphically illustrated (see Figure 4.4). While toxic assets are (monthly) sold at the beginning of the liquidation period (and selling is stopped at time $t_i^{0\rightarrow}$), well-performing assets will be liquidated (monthly) at the end of the liquidation time frame (starting at time $t_i^{\leftarrow T}$).

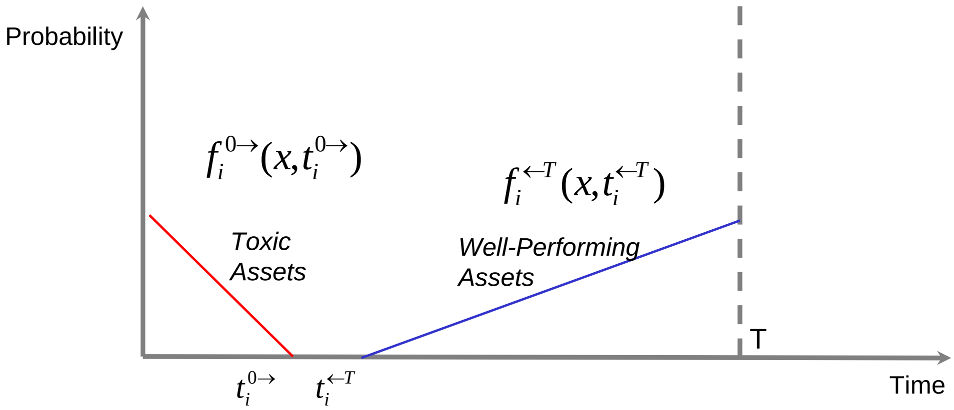

Figure 4.4: Density function for selling toxic assets (red line, left) and selling well-performing assets (blue line, right)

In order to receive the probability of an asset sale *and* the leave of the corresponding FTEs, we have to compute the convolution of the following three density functions:

(i) *The distribution of the sale of all assets:* $f_i^{0\rightarrow}$ *and* $f_i^{\leftarrow T}$ (see Figure 4.4)

(ii) *The distribution of the termination of employees:* $\hat{f}_i$ (see Figure 4.3)

(iii) *The distribution of the duration until a resigned employee leaves:* $\tilde{f}_i$ (see Figure 4.2)

This convolution ($\circ$) will provide the distribution of the duration that asset *i* will be sold *and* employee *i* leaves the company, starting at the time *t=0*. Again, expressed in density functions:

toxic assets: $$l_i^{0\rightarrow}(x,\lambda_i,T,t_i^{0\rightarrow}) = f_i^{0\rightarrow}(x,t_i^{0\rightarrow}) \circ \hat{f}_i(x) \circ \tilde{f}_i(x,\lambda_i) \qquad (4.25)$$

well-performing assets: $$l_i^{\leftarrow T}(x,\lambda_i,T,t_i^{\leftarrow T}) = f_i^{\leftarrow T}(x,t_i^{\leftarrow T}) \circ \hat{f}_i(x) \circ \tilde{f}_i(x,\lambda_i) \qquad (4.26)$$

Thus, the cumulative function of the convolution is given by:

$$L^{0\rightarrow}(x,\lambda_i,T,t_i^{0\rightarrow}) = \sum_{i=0}^{\tilde{j}} l_i^{\leftarrow T} \quad \text{and} \quad L^{\leftarrow T}(x,\lambda_i,T,t_i^{\leftarrow T}) = \sum_{i=\tilde{j}+1}^{I} l_i^{\leftarrow T}$$

$$L = L^{0\rightarrow} + L^{\leftarrow T} \qquad (4.27)$$

where $L^{0\rightarrow}$ and $L^{\leftarrow T}$ are just the unweighted sum of the convolutions $l_i^{0\rightarrow}$ and $l_i^{\leftarrow T}$ of the density functions and is thus not a density function any more.[162] This sum (*L*) is now equal to the number of FTE leaves.[163]

If we – for now – just focus on the *organizational stability*, then the FTE leaves should be completely smoothed, especially in the intersection of the two cumulated functions $L^{0\rightarrow}$ and $L^{\leftarrow T}$. Ideally, $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ are chosen in a way such that

$$L' + \varepsilon = \left[\left(L^{0\rightarrow} + L^{\leftarrow T}\right)'\right] + \varepsilon \;\cong\; \left[\left(L^{0\rightarrow} + L^{\leftarrow T}\right)'\right] - \varepsilon = L' - \varepsilon \qquad \forall \varepsilon \geq 0$$

This implies that $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ are chosen at the intersection point of $L^{0\rightarrow}$ and $L^{\leftarrow T}$ (where $+\varepsilon$ and - ε are small periods after and before the intersection, with $\varepsilon \geq 0$). This leads to the best *organizational stability*, i.e., the lowest variance in the P&L-statement.

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162 $\tilde{j}$ is the amount of assets with a negative expected mean after incorporating employee costs and is different from j, which separates toxic from well-performing assets before considering employee costs. Thus, $\tilde{j}$ is a new separator of the set of asset classes.

163 Figure 4.11, later on, shows these cumulative functions and as well as its sum L.

As derived above, we can now express the optimization problem in (4.20) of finding the best trading strategy n_t that minimizes $U(b,\hat{G})$ by looking for the best $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ for a given set of model-specification-parameters (b,λ_i,T). Hence, one can say: $n_t(t_i^{0\rightarrow},t_i^{\leftarrow T})$ where $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ are only determined by (b,λ_i,T). However, note that *b* is the sole parameter that can be chosen freely. It indicates the importance of *organizational stability* $V[G_{FTE}]$ versus the *Net Liquidation Value* $E[G]$ in equation (4.20).

4.4.3 Trading Strategy Algorithm as a Solution

At first sight, one could mistake this optimization stopping problem as a multidimensional version of the famous Secretary Problem (also know as House-Hunting Problem, Mariage-Problem or Problem of Selling Assets)[164]. However, one should note, that the *organizational stability*/smoothness (which is, besides the *Net Liquidation Value* optimization, the second potential target to achieve within the restructuring process) can only be taken into account if one considers *all* asset sales *together*. This explains why neither a separated solving for each asset class with, for example, the theory of optimal stopping time, nor the theory of dynamic programming with the Bellman equation, would lead to an optimal trading strategy for equation (4.20).[165]

Due to the absence of an existing theory that suits this problem, we will propose an intuitive new optimization algorithm. This method finds a solution for the best location of $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ that is only determined by the set (b,λ_i,T). The only parameter that can be chosen by the management is *b*, indicating the importance of the two effects:

1. *Maximizing the Net Liquidation Value*
2. *Maximizing the organizational stability*

[164] In the late 1950´s a problem, known as the Secretary-, House-Hunting-, Asset-Selling-, or Marriage- Problem, appeared in statistics. Despite its different names, the underlying question is the same: An unordered sequence of n different secretary-applicants or home-buyers, etc. are interviewed one at a time. A person, house, etc. once rejected cannot later be recalled and every additional interviews, house-visitings, etc. are associated with costs. Mosteller (1965) and Gardner (1966) solve this problem statistically and indicate the best optimal applicant. For large n it is optimal to wait until 37% have been interviewed.

[165] Bertsimas and Lo (1998) used the Bellman equation for a similar but still unresembling problem.

By varying parameter b between *Net Liquidation Value* and *organizational stability*, the management can navigate the restructuring process of its organisation according to the specific corporate requirements. Figure 4.5 illustrates this: Larger values of parameter b lead to more *organizational stability*, whereas lower values lead to less *organizational stability* but a higher *Net Liquidation Value*. Economically spoken, an organization can either focus on the P&L of the liquidation of the assets classes or on the reduction of the organizational risk that stems from the employee leaves. The parameter b allows the management of the organization to settle in between these two scenarios.

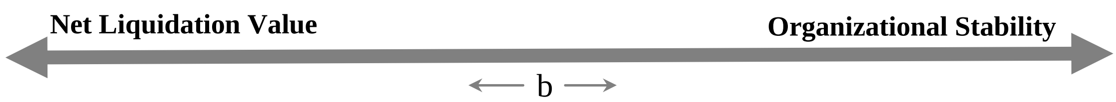

Figure 4.5: Parameter b as link between Net Liquidation Value and organizational stability

The optimal trading algorithm comprises the following three steps:

Step 1: Identify the optimal strategy to maximize the *Net Liquidation Value* alone

Set all $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ to the first and last period of the timeframe, respectively. In Figure 4.4, this would mean that the two functions are as steep as – mathematically – possible.

Step 2: Identify the optimal strategy to maximize the *organizational stability* alone

a) Smooth the intersection of the cumulated density functions $L = \left(L^{0\rightarrow} + L^{\leftarrow T}\right)$ by defining in a first step the optimal interval between the mean over all assets of $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$, i.e., the difference of $\overline{t^{0\rightarrow}} = E\left[\sum_i t_i^{0\rightarrow}\right]$ and $\overline{t^{\leftarrow T}} = E\left[\sum_i t_i^{\leftarrow T}\right]$ =: $\Delta \bar{t}$ and solve for the optimal position of $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$.

b) Maximize the target equation (4.20) to find the optimal position of $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$.

c) Spreading and widening of the overall cumulated density function L by setting $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ for some single assets unequal to its mean $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$. However, the mean of $L^{0\rightarrow}$ and $L^{\leftarrow T}$ should remain the same in order not to destroy the smoothing of L.

Step 3: Combine the strategies in step one and step two according to parameter *b*

In this section we incorporate the fact that the desired optimization problem is a combination of both strategies: *Net Liquidation Value* and *organizational stability*. Since step two has distributed $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ around its mean $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$, which implies a focus on *organizational stability*, we now need to set some of the $t_i^{0\rightarrow}$ and/or $t_i^{\leftarrow T}$ back to the first or last period to gradually increase the *Net Liquidation Value*. In order to arrange this according to the desired combination of *Net Liquidation Value* and *organizational stability* (expressed in parameter *b*) two questions arise:

a) How does the **sequence** that $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ are set to the first and last period look like?

b) For how many asset classes *i* should $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ be set to the first and last period?

We now derive the optimal liquidation algorithm in more detail, referring to the three steps outlined above.

4.4.3.1 Maximization of the *Net Liquidation Value* Only

As already mentioned in section 4.4.2, if one looks just at the *Net Liquidation Value* as target function the optimal liquidation strategy would be to set $t_i^{0\rightarrow}$ to 1 and $t_i^{\leftarrow T}$ to *T-1*.

4.4.3.2 Maximization of the *Organizational Stability* Only

Since we have to deal with a convolution of three density functions to model the fluctuation of the FTEs, the derivation of the optimal liquidation strategy for *organizational stability* only, is not straight forward and has to be performed in several steps. For simplicity and due to the additivity of the expectation operator we split the mathematical problem of the expected liquidation time. For toxic assets $i \in (1,\ j)$ we get:

$$\begin{aligned}
&\sum_i E\left\lfloor l_i^{0\rightarrow}\right\rfloor = \sum_i \left\lfloor E\left\lfloor f_i^{0\rightarrow}(x, t_i^{0\rightarrow})\right\rfloor\right\rfloor + \sum_i \left[E\left[\hat{f}_i(x) \circ \tilde{f}_i(x, \lambda_i)\right]\right] = \\
&\underbrace{E\sum_i \left[l_i^{0\rightarrow}\right]}_{L^{0\rightarrow}} = \underbrace{E\sum_i \left[f_i^{0\rightarrow}(x, t_i^{0\rightarrow})\right]}_{\overline{f_{Asset}^{0\rightarrow}}} + \underbrace{E\sum_i \left[\hat{f}_i(x) \circ \tilde{f}_i(x, \lambda_i)\right]}_{\overline{f_{FTE}^{0\rightarrow}}}
\end{aligned} \tag{4.28}$$

And for well-performing assets $i \in (I - j,\ I)$ we get:

$$\begin{aligned}
&\sum_i E\left\lfloor l_i^{\leftarrow T}\right\rfloor = \sum_i \left\lfloor E\left\lfloor f_i^{\leftarrow T}(x, t_i^{\leftarrow T})\right\rfloor\right\rfloor + \sum_i \left[E\left[\hat{f}_i(x) \circ \tilde{f}_i(x, \lambda_i)\right]\right] = \\
&\underbrace{E\sum_i \left[l_i^{\leftarrow T}\right]}_{L^{\leftarrow T}} = \underbrace{E\sum_i \left[f_i^{\leftarrow T}(x, t_i^{\leftarrow T})\right]}_{\overline{f_{Asset}^{\leftarrow T}}} + \underbrace{E\sum_i \left[\hat{f}_i(x) \circ \tilde{f}_i(x, \lambda_i)\right]}_{\overline{f_{FTE}^{\leftarrow T}}}
\end{aligned} \tag{4.29}$$

Firstly, we calculate the first part of equations (4.28) and (4.29), i.e. $E\left[f_{Asset}^{0\rightarrow}\right]$ and $E\left[f_{Asset}^{\leftarrow T}\right]$. This problem is equivalent to the problem of finding z of the following equations:

$$E\left[f_{Asset}^{0\rightarrow}\right] = z^{0\rightarrow} \quad \Leftrightarrow \quad \int_0^{z^{0\rightarrow}} f^{0\rightarrow}(x, t^{0\rightarrow})\,dx = \int_0^{z^{0\rightarrow}} \left[-2\frac{1}{(t^{0\rightarrow})^2}x + \frac{2}{t^{0\rightarrow}}\right]dx = 0.5 \tag{4.30}$$

$$z^{0\rightarrow} = t^{0\rightarrow} - \frac{t^{0\rightarrow}}{\sqrt{2}}$$

and

$$E\left[f_{Asset}^{\leftarrow T}\right] = z^{\leftarrow T} \quad \Leftrightarrow \quad \int_{z^{\leftarrow T}}^{T} f^{\leftarrow T}(x, t^{\leftarrow T})\,dx = \int_{z^{\leftarrow T}}^{T} \left[\frac{2}{(t^{\leftarrow T})^2}x - \frac{2}{(t^{\leftarrow T})^2}T + \frac{2}{t^{\leftarrow T}}\right]dx = 0.5 \tag{4.31}$$

$$z^{\leftarrow T} = T - t^{\leftarrow T} \cdot \left(1 - \frac{1}{\sqrt{2}}\right)$$

Secondly, we focus on the second part in equations (4.28) and (4.29). In order to increase the smoothness of restructuring at the intersection of both asset classes, $t_i^{0\rightarrow}$ (the latest liquidation time of toxic assets) and $t_i^{\leftarrow T}$ (the earliest liquidation time of well-performing assets) have to be chosen such that the two cumulated density functions of $L^{0\rightarrow}$ and $L^{\leftarrow T}$ overlap in the best, i.e., smoothest way possible.

$$\overline{t^{0\rightarrow}} = E\left[\sum_i t_i^{0\rightarrow}\right] \text{ and } \overline{t^{\leftarrow T}} = E\left[\sum_i t_i^{\leftarrow T}\right]$$

Ideally they should add up in a way that one sees neither a 'peak' nor a 'hole' in the area of intersection. A 'hole' would appear if $L^{0\rightarrow}$ and $L^{\leftarrow T}$ are completely disjunct. A 'peak' would accrue if $L^{0\rightarrow}$ and $L^{\leftarrow T}$ would intersect such that the cumulated maximum is bigger than the maximum of $L^{0\rightarrow}$ or $L^{\leftarrow T}$. A perfectly smooth intersection could be expressed as

$$L' + \varepsilon \cong L' - \varepsilon \quad \forall \varepsilon > 0$$

at the point of the intersection of $L^{0\rightarrow}$ and $L^{\leftarrow T}$. Both cumulative functions $L^{0\rightarrow}$ and $L^{\leftarrow T}$ of the convolution of the set of density functions consist of one fraction ($\overline{f_{Asset}^{0\rightarrow}}$) for the asset liquidation of toxic asset classes and another fraction ($\overline{f_{Asset}^{\leftarrow T}}$) for well-performing assets classes. Figure 4.6 shows a typical shape of the different fractions of the two cumulative functions and illustrates how they overlap. ($\Omega_{\overline{f(.)}}$ denotes the set of all density functions.)

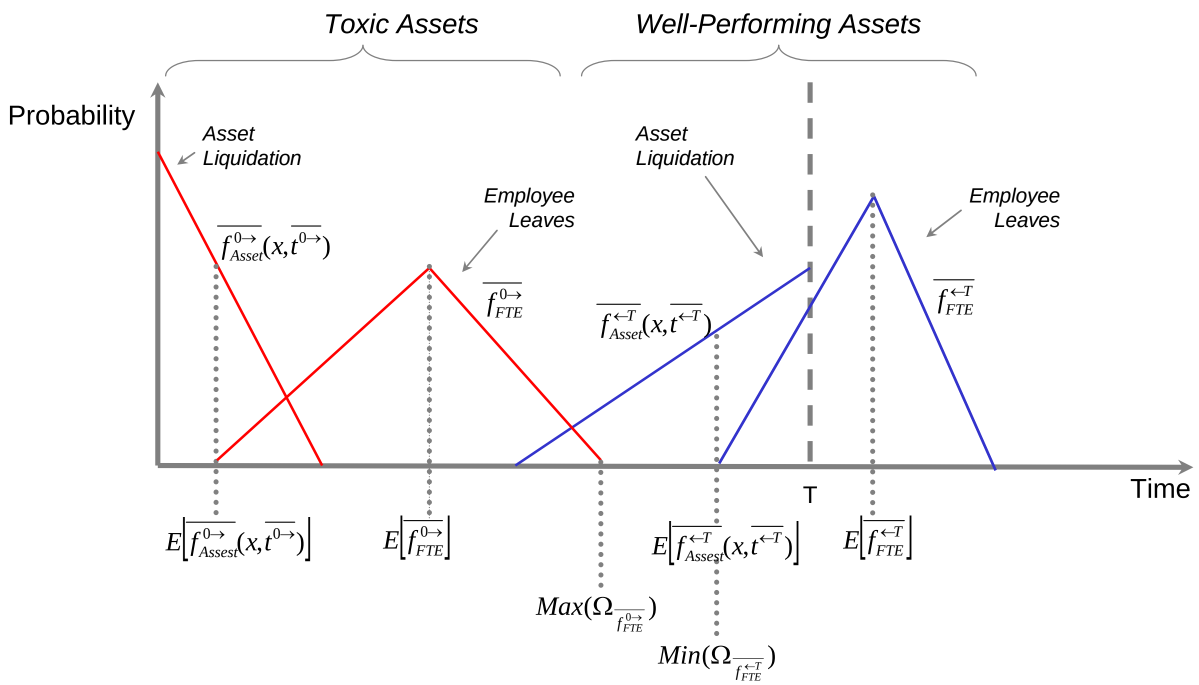

Figure 4.6: Schematic illustration of the density functions for toxic and well-performing assets

(a) The first step is to get a smooth intersection between the two cumulative functions $L^{0\rightarrow}$ and $L^{\leftarrow T}$. Therefore, one has to calculate for both cumulative functions the half of the height of the highest point. As illustrated in Figure 4.7 and 4.8, we need the half of the height as a first step to get to the point where the height of $\overline{f}_{FTE}^{\leftarrow T}$ and $\overline{f}_{FTE}^{0\rightarrow}$ are equal. This is then the point of the smoothest intersection of the two cumulative functions. By approximating the convolution of $\overline{f}_{FTE}^{\leftarrow T}$ and $\overline{f}_{FTE}^{0\rightarrow}$ with lines[166], one can employ the Theorem on Intersecting Lines[167] to find the points

$$\frac{1}{2}Max\left[\overline{f}_{FTE}^{\leftarrow T}\right] \quad \text{and} \quad \frac{1}{2}Max\left[\overline{f}_{FTE}^{0\rightarrow}\right]$$

on the abscissa.

For toxic assets $i \in (1, j)$ we receive, as graphically shown in Figure 4.7:

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166 Note that the convolution is not, besides the trivial case where $\lambda = 0$, a function with straight lines, but a function with second order polynoms.

167 Application of the theorem of intersecting lines for the approximation of

$$Max[f_i(\lambda_i,t)] : \left[\left[\sum_{t\in(0,T)} full\ definition - area\ of\ f_i(\lambda_i,t)\right] - E[f_i(\lambda_i,x)]\right] = \frac{1}{2}Max[f_i(\lambda_i,x)] : [\tau_i - E[f_i(\lambda_i,x)]]$$

$$\mathrm{TA} = \mathrm{E}\left[\overline{\mathrm{f}_{\mathrm{FTE}}^{0\rightarrow}}\right] + \frac{\mathrm{Max}(\Omega_{\overline{\mathrm{f}_{\mathrm{FTE}}^{0\rightarrow}}}) - \mathrm{E}\left[\overline{\mathrm{f}_{\mathrm{FTE}}^{0\rightarrow}}\right]}{2}$$

and for well-performing assets $i \in (I - j, I)$, also illustrated in Figure 4.7, we get:

$$\mathrm{WAP} = \mathrm{E}\left[\overline{\mathrm{f}_{\mathrm{FTE}}^{\leftarrow\mathrm{T}}}\right] - \frac{\overbrace{\left(\mathrm{Min}(\Omega_{\overline{\mathrm{f}_{\mathrm{FTE}}^{\leftarrow\mathrm{T}}}})\right)}^{=\mathrm{E}\left[\overline{\mathrm{f}_{\mathrm{Asset}}^{\leftarrow\mathrm{T}}}(\mathrm{x},\overline{\mathrm{t}^{\leftarrow\mathrm{T}}})\right]} + \mathrm{E}\left[\overline{\mathrm{f}_{\mathrm{FTE}}^{\leftarrow\mathrm{T}}}\right]}{2}.$$

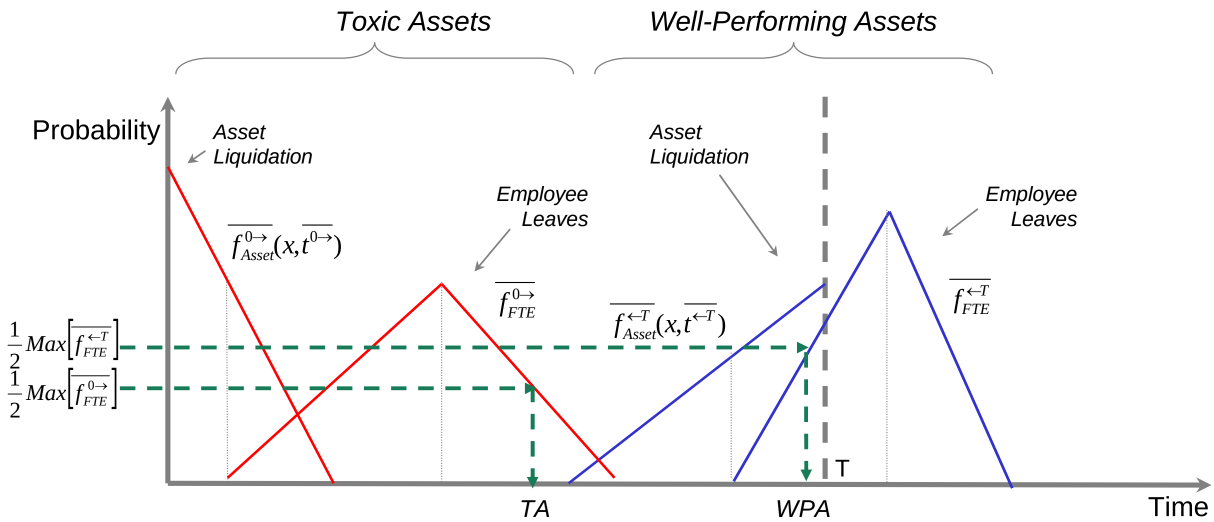

Figure 4.7: Determination of points where the convolution of the FTE-density functions is half as high as the highest point

In using the average of $\frac{1}{2}Max\left[\overline{f_{FTE}^{\leftarrow T}}\right]$ and $\frac{1}{2}Max\left[\overline{f_{FTE}^{0\rightarrow}}\right]$, i.e.

$$\mathrm{PAH} = \frac{\frac{1}{2}\mathrm{Max}\left[\overline{\mathrm{f}_{\mathrm{FTE}}^{\leftarrow\mathrm{T}}}\right] + \frac{1}{2}\mathrm{Max}\left[\overline{\mathrm{f}_{\mathrm{FTE}}^{0\rightarrow}}\right]}{2}$$

we get the time points $\overline{\tau^{0\rightarrow}}$ and $\overline{\tau^{\leftarrow T}}$ (see Figure 4.8). $\overline{\tau^{0\rightarrow}}$ and $\overline{\tau^{\leftarrow T}}$ are two points in time where the two cumulative functions $L^{0\rightarrow}$ and $L^{\leftarrow T}$ have the same height.

The perfect intersection point of $L^{0\rightarrow}$ and $L^{\leftarrow T}$ is the point where $L = \left(\underline{L^{0\rightarrow} + L^{\leftarrow T}}\right)$ equals the sum of half the height of the highest point of the density functions $\overset{\leftarrow T}{f_{FTE}}$ and $\overset{0\rightarrow}{f_{FTE}}$. This implies that $(\overline{\tau^{\leftarrow T}} - \overline{\tau^{0\rightarrow}})$ → 0.

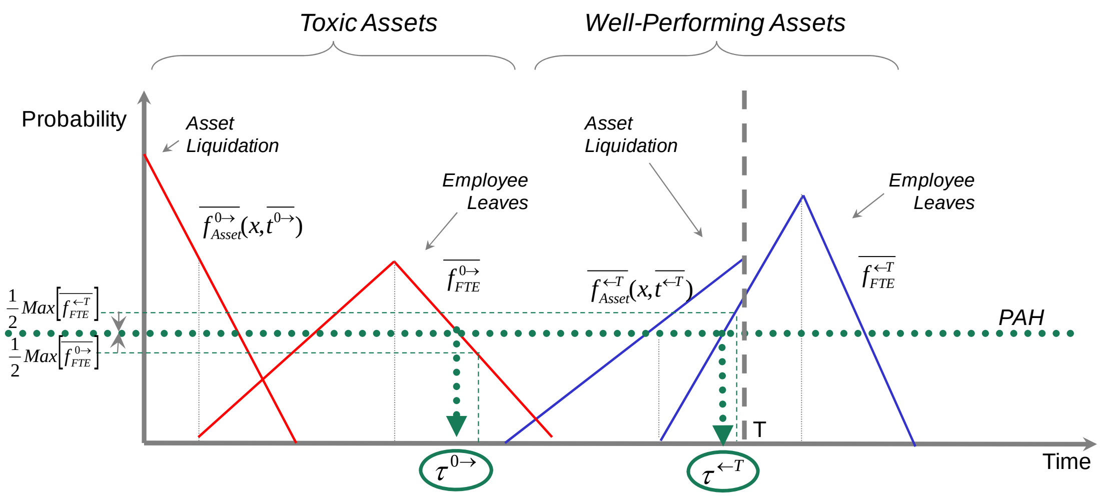

Figure 4.8: Definition of the points that should ideally merge, i.e. $(\overline{\tau^{\leftarrow T}} - \overline{\tau^{0\rightarrow}})$ → 0

To calculate $\overline{\tau^{\leftarrow T}}$ *and* $\overline{\tau^{0\rightarrow}}$, we again need the Theorem of Intersecting Lines, as shown in Figure 4.9:

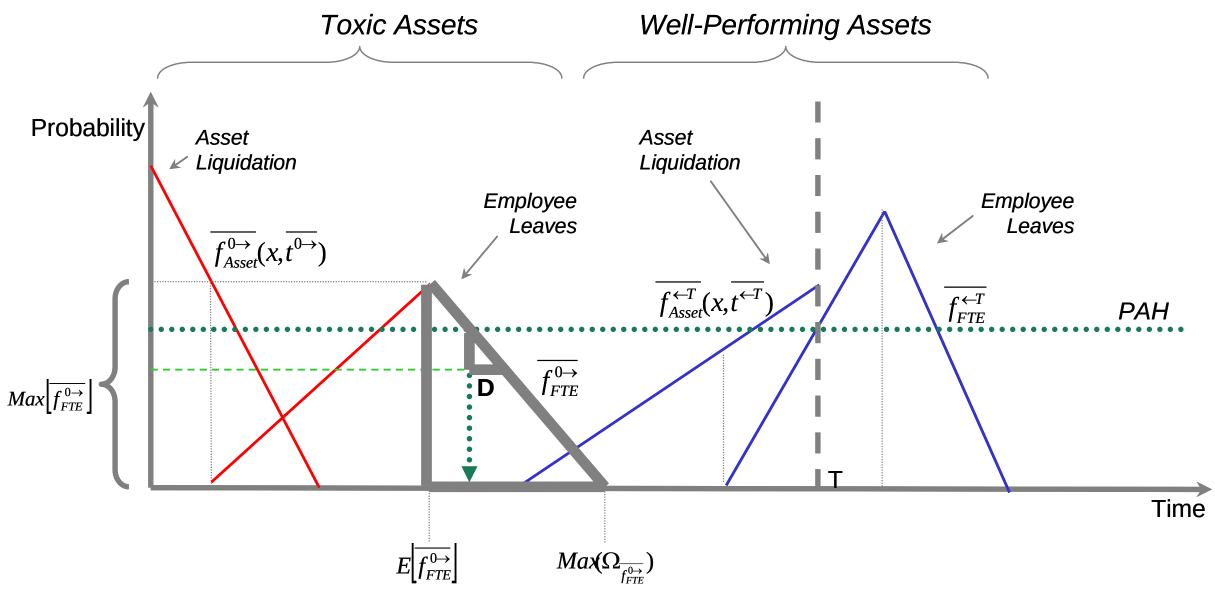

Figure 4.9: Calculation of the variable D with of the theorem on intersecting lines to further specify the perfect point of intersection

According to the Theorem of Intersecting Lines, we need to calculate distance D as new variable:

$$\frac{Max(\Omega_{\overline{f^{0\rightarrow}_{FTE}}}) - E\left[\overline{f^{0\rightarrow}_{FTE}}\right]}{Max\left[\overline{f^{0\rightarrow}_{FTE}}\right]} = \frac{D}{\left[\dfrac{\frac{1}{2}Max\left[\overline{f^{\leftarrow T}_{FTE}}\right] + \frac{1}{2}Max\left[\overline{f^{0\rightarrow}_{FTE}}\right]}{2}\right] - \frac{1}{2}Max\left[\overline{f^{0\rightarrow}_{FTE}}\right]}$$

Having specified this distance D (see Figure 4.9), one can calculate $\overline{\tau^{\leftarrow T}}$ *and* $\overline{\tau^{0\rightarrow}}$ as:

$$\overline{\tau^{0\rightarrow}} = z^{0\rightarrow} + \frac{Max(\Omega_{\overline{f^{0\rightarrow}_{FTE}}}) - E\left[\overline{f^{0\rightarrow}_{FTE}}\right]}{2} - \frac{Max(\Omega_{\overline{f^{0\rightarrow}_{FTE}}}) - E\left[\overline{f^{0\rightarrow}_{FTE}}\right]}{Max\left[\overline{f^{0\rightarrow}_{FTE}}\right]} \cdot \left\langle \left[\frac{\frac{1}{2}Max\left[\overline{f^{\leftarrow T}_{FTE}}\right] + \frac{1}{2}Max\left[\overline{f^{0\rightarrow}_{FTE}}\right]}{2}\right] - \frac{1}{2}Max\left[\overline{f^{0\rightarrow}_{FTE}}\right] \right\rangle$$

$$\overline{\tau^{\leftarrow T}} = z^{\leftarrow T} - \frac{\overbrace{\left(Min(\Omega_{\overline{f^{\leftarrow T}_{FTE}}})\right)}^{=E\left[\overline{f^{\leftarrow T}_{Asset}}(x,\overline{t^{\leftarrow T}})\right]} + E\left[\overline{f^{\leftarrow T}_{FTE}}\right]}{2} - \frac{Min(\Omega_{\overline{f^{\leftarrow T}_{FTE}}}) - E\left[\overline{f^{\leftarrow T}_{FTE}}\right]}{Min\left[\overline{f^{\leftarrow T}_{FTE}}\right]} \cdot \left\langle \left[\frac{\frac{1}{2}Max\left[\overline{f^{\leftarrow T}_{FTE}}\right] + \frac{1}{2}Max\left[\overline{f^{0\rightarrow}_{FTE}}\right]}{2}\right] - \frac{1}{2}Min\left[\overline{f^{\leftarrow T}_{FTE}}\right] \right\rangle$$

These two equations only depend on $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$ that implicitly determine the position of $\overline{f^{0\rightarrow}_{Asset}}$, $\overline{f^{\leftarrow T}_{Asset}}$ and $\overline{f^{0\rightarrow}_{FTE}}$, $\overline{f^{\leftarrow T}_{FTE}}$ respectively. Hence, by solving this system of two equations, it is easy to calculate $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$ such that $(\overline{\tau^{\leftarrow T}} - \overline{\tau^{0\rightarrow}})$ → 0.

(b) In a second step, we have to indicate the adequate liquidation strategy expressed in $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$ or $\overline{\Delta t} = (\overline{t^{\leftarrow T}} - \overline{t^{0\rightarrow}})$ in order to achieve an optimal intersection of the density functions $L^{0\rightarrow}$ and $L^{\leftarrow T}$ (see equation (4.27)) such that $(\overline{\tau^{\leftarrow T}} - \overline{\tau^{0\rightarrow}})$ *= 0.*

Note that the optimization algorithm so far has just optimized $\overline{\Delta t} = (\overline{t^{\leftarrow T}} - \overline{t^{0\rightarrow}})$, but not the position of $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$ itself. This straight forward optimization can be solved via the target function (maximizing the expected *Net Liquidation Value*):

$$\underset{t^{0\rightarrow}}{Max}\, E[G]$$

under the constraints

$$\overline{t^{0\rightarrow}} \geq 0 \text{ and } \overline{t^{\leftarrow T}} = \overline{t^{0\rightarrow}} + \overline{\Delta t}.$$

Likewise this problem can also be solved by maximizing $\overline{t^{\leftarrow T}}$.

Thus, the initial position of $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$ are changed as long as $\overline{\tau^{\leftarrow T}} = \overline{\tau^{0\rightarrow}}$ *(see* Figure 4.10).

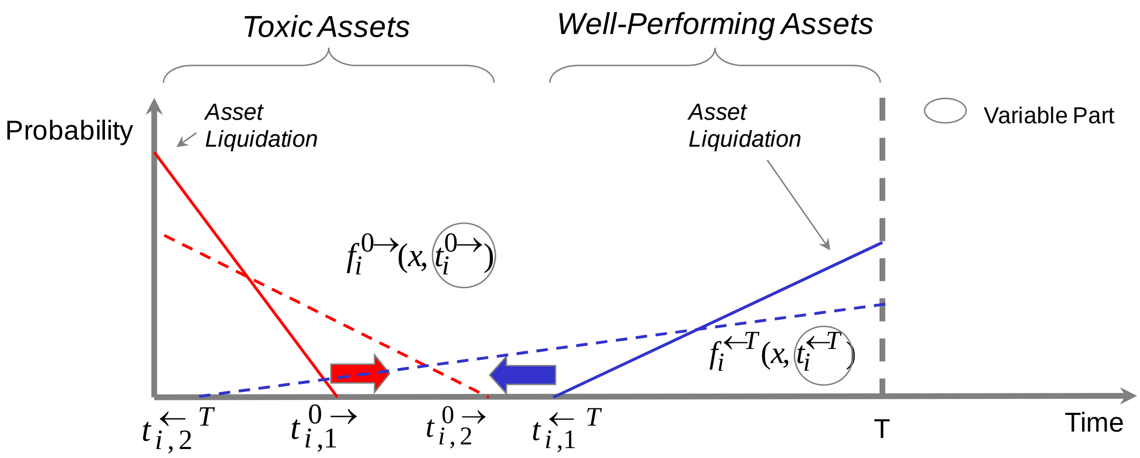

Figure 4.10: Change of $\overline{t^{0\to}}$ and $\overline{t^{\leftarrow T}}$ to get a smooth intersection of $L^{0\to}$ and $L^{\leftarrow T}$

Since an employee only leaves the organization after her asset class has been sold, it is obvious that a change in the maximum or minimum liquidation time $t_i^{0\to}$ and $t_i^{\leftarrow T}$ (and consequently in the expected mean of all $\overline{t^{0\to}}$ and $\overline{t^{\leftarrow T}}$, as well as in the asset liquidation density functions $\overline{f_{Asset}^{0\to}}$ and $\overline{f_{Asset}^{\leftarrow T}}$) directly influences the starting position of the density functions for the employee leaves $\overline{f_{FTE}^{0\to}}$ and $\overline{f_{FTE}^{\leftarrow T}}$. According to equation (4.27), these changes determine the cumulative functions $L^{0\to}$ and $L^{\leftarrow T}$, as they are the sum of the convolution of the three density functions (see equation (4.25)-(4.27)).

As Figure 4.11 illustrates, this generates a function L with no "holes" or "peaks" at the intersection.

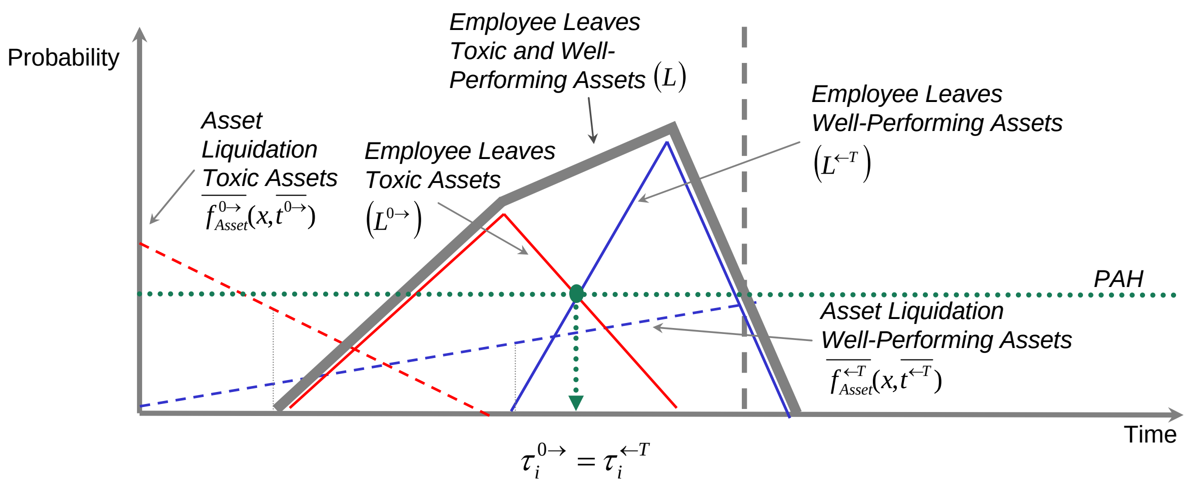

Figure 4.11: Smooth intersection of $L^{0\to}$ and $L^{\leftarrow T}$

(c) The third step of the derivation of the optimal liquidation algorithm in terms of *organizational stability* is trying to obtain even a better *organizational stability* by changing the convolutions of function *L*. So far, the algorithm has just specified one $\overline{t^{0\rightarrow}}$ for all toxic assets and one $\overline{t^{\leftarrow T}}$ for all well-performing assets that lead to a smooth intersection of $L^{0\rightarrow}$ and $L^{\leftarrow T}$. The idea is to obtain even a smoother liquidation and restructuring of the employees, i.e., a wider spread function *L*, when we set for some assets *i* the correspondent $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ to another value than just the average values $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$. Nevertheless, the mean of all $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ should remain at the initial value of $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$, because otherwise we would loss the perfectly smooth intersection of $L^{0\rightarrow}$ and $L^{\leftarrow T}$, which we derived in step 2 above. This requirement can be expressed as followed:

$$\overline{t^{0\rightarrow}} = E\left[\sum_i t_i^{0\rightarrow}\right] \text{ and } \overline{t^{\leftarrow T}} = E\left[\sum_i t_i^{\leftarrow T}\right]$$

For the same argument and as developed in chapter 4.4.2, it is more profitable to sell the assets with a higher expected profit, i.e. $[\mu_i x_i - c_i]$, at a later stage of the process. According to the rank of $[\mu_i x_i - c_i]$, $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ should be distributed *around* the means $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$ in equidistance between

$$\left(0,\ 2\cdot\overline{t^{0\rightarrow}}\right) \text{ and } \left(T-2\cdot\overline{t^{\leftarrow T}},\ T\right).$$

Note that, $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$ are still the mean of these intervals.

This procedure ensures on the one hand the means $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$, and, therefore, the smoothed intersection of $L^{0\rightarrow}$ and $L^{\leftarrow T}$, remain the same and on the other hand asset and employee restructuring will be spread as wide as possible over the potential interval.

4.4.3.3 Combined Optimization: *Net Liquidation Value* versus *Organizational stability*

Organizational stability is typically not the only aim of the management. It is more likely that the management prefers a combination of *organizational stability* and *Net Liquidation Value* maximization. As already defined in equation (4.20), parameter $b \in [0, \infty]$ indicates whether *organizational stability or Net Liquidation Value G* is more important for the management. A large parameter *b* puts more focus on the *organizational stability*, whereas a small *b* indicates that the *Net Liquidation Value* is more important for the decision maker.

For extreme values of *b,* i.e., $b = 0$ or $b = \infty$, the trading strategies $n_t(t_i^{0\rightarrow},\ t_i^{\leftarrow T})$ are already derived above (see steps one (section 4.4.3.1) and two (section 4.4.3.2) of this algorithm). However, we have not yet solved the optimization problem for $0 < b < \infty$.

By rearranging the parameter b of the target function (4.20) we get:

$$B = \frac{b^2 V[G_{FTE}]}{E(G)} \in [0,\ \infty]$$

This equation means that the *organizational stability $V[G_{FTE}]$* is *B*-times more or less important than the *Net Liquidation Value E(G).* For simplification purposes, we cap the maximum of *B* at B_{MAX}.[168] This approach defines a closed interval for parameter *B* (instead of an infinite one as stated above) and simplifies the numeric calculation. In the next chapter we set B_{MAX} to 10, which means that *B* can be chosen between 0 (only focus on the *Net Liquidation Value*) and 10 (only focus on the *organizational stability*).

Starting from B_{MAX}, i.e., a trading strategy that optimizes only the *organizational stability*, we set for decreasing *B* $t_i^{0\rightarrow}$ (for each asset i) to the first period ($t_i^{0\rightarrow}$ = 1) and $t_i^{\leftarrow T}$ to the period *(T-1).* By decreasing B we put gradually more and more focus on the *Net Liquidation Value*. The more *B* approaches zero, the more important the *Net Liquidation Value* becomes compared to *organizational stability*.

168 By employing a cap, we set all $B \geq B_{MAX}$ at B_{MAX}.

To complete this optimal trading algorithm, two questions still remain: (i) In what sequence should $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ be set between 1 and (T-1) and (ii) for how many assets *i* should the trading time $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ be set to 1 and (T-1)? To answer these questions it is important to reach the desired position between the *Net Liquidation Value* and the *organizational stability* according to parameter *B*.

Ad (i) The sequence of assets, for which we set $t_i^{0\rightarrow}$ to 1 and $t_i^{\leftarrow T}$ to *(T-1)*, (i.e. the optimal solution of the *Net Liquidation Value* target function) is drawn from a rank system of the expected return of the assets: All assets $i \in I$ are ranked according to its expected profit/loss, i.e., according to $[\mu_i x_i - c_i]$. We define the parameter $\hat{i}$ as the index of the ranked assets. E.g., $\hat{i}$ *=1* equals the asset with the lowest and $\hat{i}$ *=I* with the highest value of $[\mu_i x_i - c_i]$.

The effect of this 'stretching' according to the stretching parameter *C* (scaled from 0-10) on the density function and distribution function is expressed graphically in Figure 4.12. [169]

[169] Model specifications for the following Figures: Execution time ($\overline{t^{0\rightarrow}}$, $\overline{t^{\leftarrow T}}$), density functions and sales distribution functions are optimized in the optimization algorithm. Liquidation period *T = 40* (could be, for instance, 2 years). (However, the leave of the employees can occure later than the last asset liquidation.). Number of asset class are *I = 40*, where each asset class is modeled as a Random Walk with random probabilities for "up" and "down" and, thus, for the drift and the volatility, however i toxic assets (*i = 25*) are modeled to have a higher probability of a down step and, vice versa, well-performing assets (*I-i = 15*) have a higher probability of an up step. The Markov Switching probabilities for the i toxic assets are a *55%* probability to stay in the same regime over the whole liquidation period (as in starting time *t = 0*), a *40%* probability to switch to a regime of even lower expected drift over the whole liquidation period T, and a *5%* probability for an increasing expected drift within T (compare BCG (2009)). Personnel costs per FTE (full time employee) for one year (T/2) are equally distributed between *100 k* and *300 k* money units. Each FTE is managing 25 Mio of assets, which means that every portfolio manager has to generate a profit of more than *80 bps* p.a. to justify her assignment. Stretching-parameter C of the optimization algorithm is constantly set to 0 and to 10. Exponential price impact functions are used.

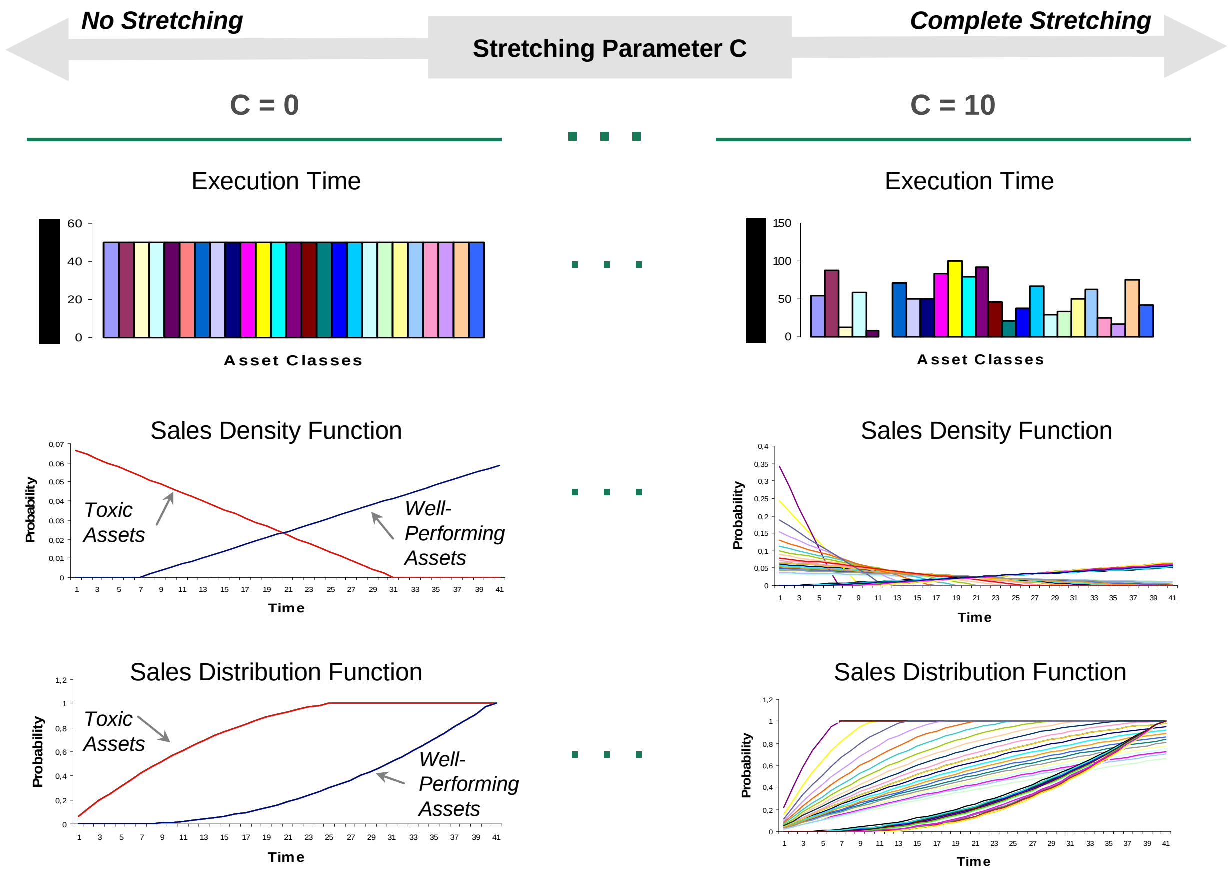

Figure 4.12: Expected maximal execution time ($\overline{t^{0\rightarrow}}$,$\overline{t^{\leftarrow T}}$), density functions of the asset sales ($f_i^{0\rightarrow}$, $f_i^{\leftarrow T}$) and their distribution functions for different stretching parameters C

The left hand side of the graphic represents an execution with no stretching (C = 0; all $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$ are set to the mean values ($\overline{t^{0\rightarrow}}$,$\overline{t^{\leftarrow T}}$)), whereas the right hand side illustrates an execution with complete stretching (C = 10; all $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ are set to a different value than the initial means $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$). Considering the execution process with no and complete stretching, we state that stretching leads to a more volatile execution time. With no stretching, the density functions of all assets have the same shape. The sales distribution functions are the distribution function according to the corresponding sales density functions.

Figure 4.12 shows the effect of stretching parameter *C* on the maximum execution time, as well as the different density and distribution functions. Obviously, the larger the stretching parameter *C* the more volatile is the execution process of all assets. Note that the difference between parameters *C* and *B* is that the stretching parameter *C* distributes the different $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ around a fixed expected means $\overline{t^{0\rightarrow}}$ and $\overline{t^{\leftarrow T}}$, whereas parameter *B* indicates how many $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ are set to the first and last period, which will be described in (ii).

Ad (ii) With parameter *B* the management of the organization defines how important *organizational stability* is compared to the *Net Liquidation Value*. In mathematical terms this implies for how many assets *i* $t_i^{0\rightarrow}$ and $t_i^{\leftarrow T}$ have to be set to period one or to period *(T-1)*, respectively. Note that for $B \geq B_{MAX}$ none of the $t_i^{0\rightarrow}$ or $t_i^{\leftarrow T}$ and for $B = 0$ all of the $t_i^{0\rightarrow}$ or $t_i^{\leftarrow T}$ are set to *1* or *(T-1)*, respectively. We define *k* with $0 \leq k \leq I$ as the numbers of assets of the ranked list that are set to *1* or to *(T-1)*, respectively. *k is* drawn out of the following equation:

$$\underset{0 \leq k \leq I}{Arg\,Min} \left| \sum_{\hat{i}=1}^{k} \left[\mu_{\hat{i}} x_{\hat{i}} - c_{\hat{i}} \right] - \frac{Min(B, B_{MAX}) - B_{MAX}}{B_{MAX}} \cdot \sum_{i=1}^{I} \left[\mu_i x_i - c_i \right] \right| \rightarrow k$$

Having introduced this optimization algorithm, we now can calculate an optimal trading strategy $n_t(t_i^{0\rightarrow}, t_i^{\leftarrow T})$ which is only determined by (b, λ_i, T) for every time step *t*. [170]

4.5 Results and Numerical Comparison

In this section we present the main numerical results of our model, introduced in section four. The model contributes to the literature in linking asset- and organizational-restructuring. It also answers many practical questions arising in times of a crisis. Often managers question how to guide their organizations through a necessary restructuring process. In addition, involved states have to review the restructuring plans (e.g., within an EU State Aid Process) and have to cope with unemployment compensation.

Our most important finding is that the combined modelling of asset liquidation and organizational restructuring has big advantages for the corresponding firm. Assuming a given liquidation time T and an execution portfolio with drift and volatility expectations for each asset $i \in I$ in every Markov Switching Regime, and an exponential price impact function, we simulate via a Monte Carlo Simulation approach the best liquidation strategy for a given parameter B. This parameter B represents the degree of freedom for the management that can be utilized as a manipulative variable to switch between strategies on the frontier of optimized liquidation sequences.

[170] This optimization has to be performed every time step since the expected profit/loss of asset *i* can change as the price processes incorporates structural breaks.

Numerically, we are able to show that the model can smoothen the restructuring in terms of labour reorganization. However, the model does not neglect the P&L-Effect, i.e., the *Net Liquidation Value*, of a potential restructuring plan. Thus, our contribution improves the restructuring process (i) from an organizational (*microeconomic*) viewpoint and (ii) from an economical (*macroeconomic*) point of view.

(i) Microeconomic view: The positive effects of this model are:

First, the model lowers the risk of organizational disruption by smoothening the process of staff reduction and, thus, avoiding peaks of labour leaves. Figure 4.13 provide the expected leaves of employees whereas Figure 4.14 shows the corresponding numerical results and show how the model can smoothen the leaves of employees over time. Panel A of Figure 4.13 (Figure 4.14) present the expected leaves of employees (in *full term employee*s (FTE)) if the management does not incorporate *organizational stability* (i.e. only the *Net Liquidation Value* is maximized). In contrast, Panel B of Figure 4.13 (Figure 4.14) shows how our model smoothes the expected leaves of employees within the given timeframe T (in our example: T = 40 periods[171]) when *organizational stability* is incorporated. These results point out how organisational risk and P&L of asset liquidation can be modelled and optimized at the same time.

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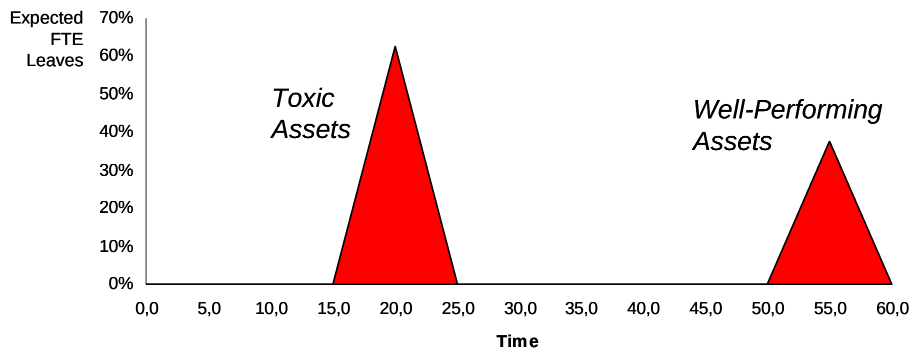
[171] Note that *T* refers to the liquidation period of assets excluding the required time period for employee resignment and leave.

Figure 4.13: Expected FTE-leaves

Panel A depicts the case without consideration of *organizational stability*, and Panel B shows the results for an *organizational stability* parameter B = 10 = B_{max} which means a maximum focus on the *organizational stability*.

Panel A: *Net Liquidation Value* only



Panel B: *Net Liquidation Value* AND *organizational stability*

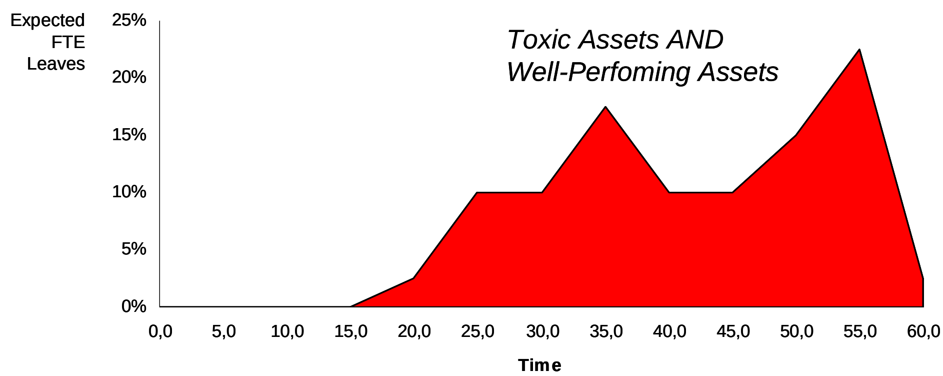
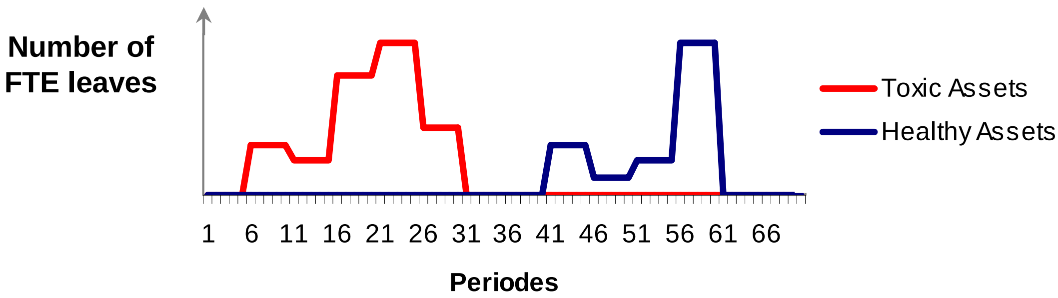


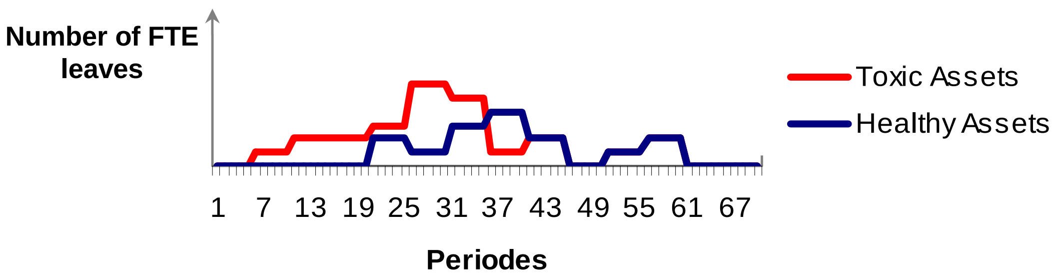
Figure 4.14: Differences in the simulated FTE-leaves according to the asset type

Panel A shows FTE leave optimization with *Net Liquidation Value* only (without consideration of *organizational stability*), and Panel B exhibits for *Net Liquidation Value* plus a maximum focus on *organizational stability* with an *organizational stability* parameter B = 10 = B_{max}.

Panel A: *Net Liquidation Value* only



Panel B: *Net Liquidation Value* AND *organizational stability*

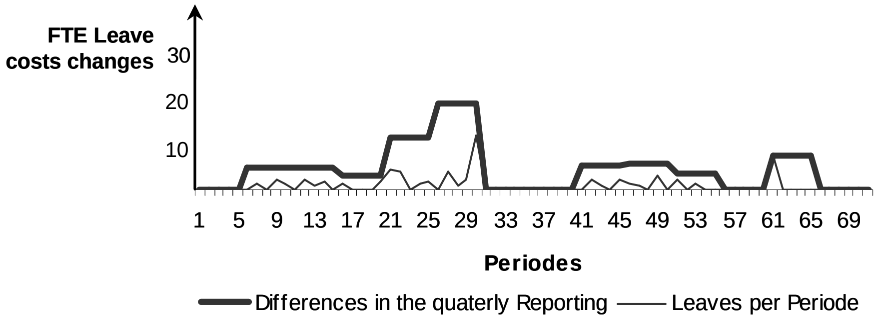


Modelling the *Net Liquidation Value* only or together with *organizational stability* influences also the corresponding costs and, thus, also the quarterly P&L of the personal costs. Figure 4.15 presents in this respect the changes in quarterly costs for full time employee (FTE) leaves for a liquidation period of two years (T=40). Panel A of Figure 4.15 shows the simulated costs when the model is not used and Panel B illustrates the results when using the model. Considering the scales of Panel A and B, one can see that, if the model is utilized (Panel B), the changes of costs for employees are wider spread and, thus, the organisational restructuring proceeds smoother.

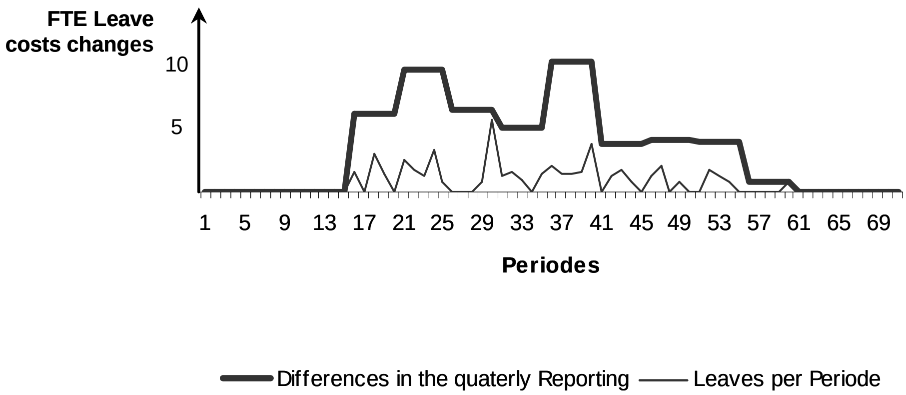
Figure 4.15: Differences in the simulated FTE-cost changes

Panel A depicts the results without our optimization model (where we show any random realization of the stochastic processes), and Panel B shows the results when asset liquidation and *organizational stability* are optimized together.

Panel A: *Net Liquidation Value* only



Panel B: *Net Liquidation Value* AND *organizational stability*



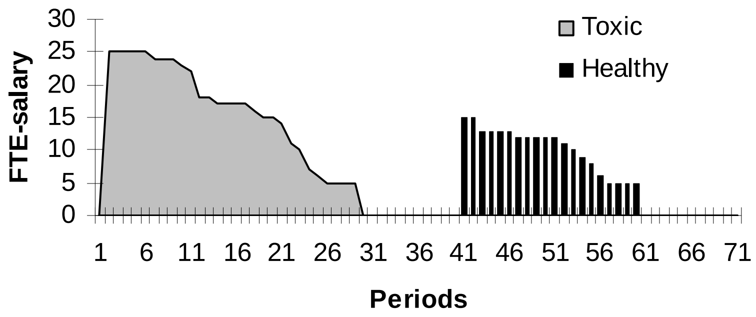
Second, the model enables to lower the (maximum) relative amount of staff that has no asset class to manage (i.e., their asset class already has been sold). Figure 4.16 demonstrates in this respect the decreasing probability of peaks in FTE-leaves[172], which can be interpreted as an increasing *organizational stability*. Panel A of Figure 4.16 shows the expected FTE-leaves when the management only focus on the P&L of the asset liquidation. In contrast, Panel B demonstrates how the model can decrease the probability of peaks by overlapping the expected FTE-leave distribution.

[172] A FTE-peak refers a situation within the restructuring process where a relatively large amount of employees leave the organization in (almost) the same timeframe.

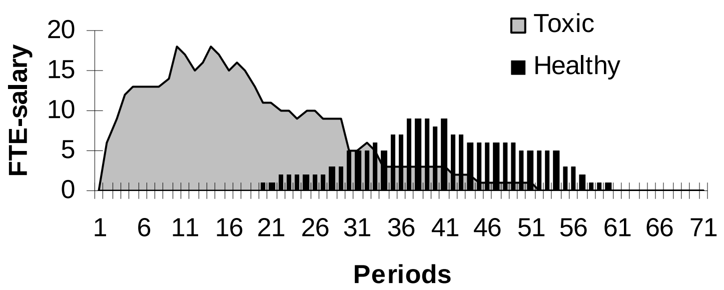
Figure 4.16: Simulated salary of FTEs with no asset class to manage

Panel A depicts the results without our optimization model, and Panel B shows the results when asset liquidation and *organizational stability* are optimized together.

Panel A: *Net Liquidation Value* only



Panel B: *Net Liquidation Value* AND *organizational stability*



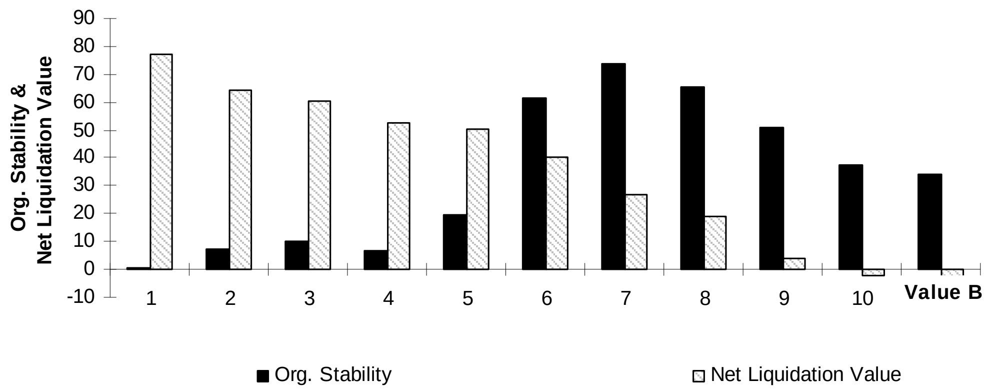
Third, the model enables to significantly increase both the *organizational stability* and the *Net Liquidation Value* compared to the best practice, the Up&Out and Down&Out strategy, which is currently used in the asset sale of most Bad Banks. Figure 4.17 shows that even after optimizing the Up&Out and Down&Out Strategy (Panel B) by setting the barriers wisely[173], our new model (Panel A), leads - on average - to significantly better results for the *Net Liquidation Value* (grey bars) and *organizational stability (black bars).* The y-axis indicates the value of the *Net Liquidation Value* and *organisational stability,* expressed in currency units. In Panel A, we show the results for *Net Liquidation Value* and *organizational stability* for all possible values of the parameter B (on the x-axis), which shifts the focus between the *Net Liquidation Value* and the *organizational stability,* as described above. In Panel B, we calculate *Net Liqudation Value* and *organizational stability* for different barriers (on the x-axis). The barrier number on the x-axis indicates how many percentage points the up- or down-barrier is above or below the initial starting value of the stochastic process of the assets. Comparing no matter what point of the x-axis, our new model (Panel A), is better than the current industry-wide best practice (Panel B) in terms of height of the bars, i.e. the *Net Liquidation Value* and the *organizational stability,* illustrated on the y-axis of Figure 4.17.

[173] Using a Monte Carlo Simulation, one can find the best upper and lower barrier that optimize the *Net Liquidation Value*.

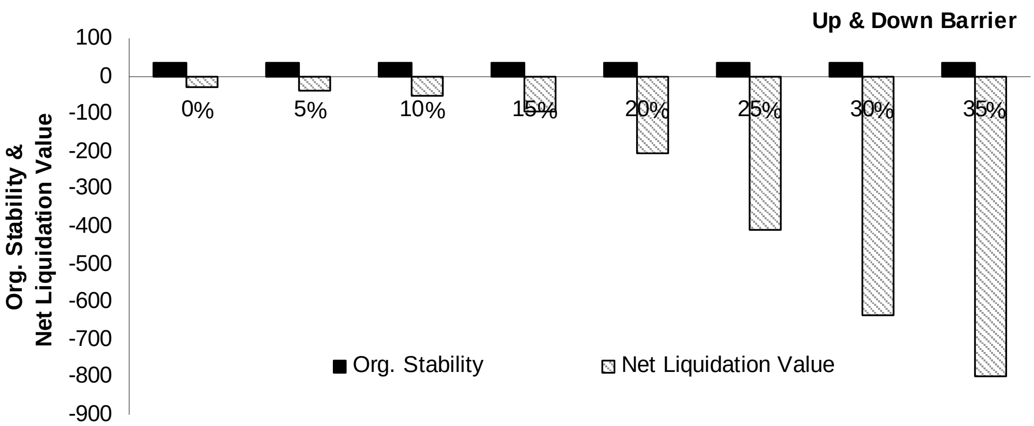
Figure 4.17: *Net Liquidation Value* & *organizational stability* modelling vs. best practice Up&Out and Down&Out-Strategy

Panel A depicts the results without our optimization model, and Panel B shows the results when asset liquidation and *organizational stability* are optimized together.

Panel A: *Net Liquidation Value* & *organizational stability*



Panel B: Up&Out and Down&Out Strategy - Current best Practice



In analogy to the commonly used ´Risk-Return´ concept, we illustrate in Figure 4.18 the simulation results on a *Net Liquidation Value* (comparable to ´Return´) and *organizational persistence* (comparable to ´Risk´) coordinate system. It shows that by applying the Up&Out and Down&Out Strategy, management can only influence the *Net Liquidation Value* (by varying the Up and Down Barrier), whereas the *organizational persistence* stays constant throughout the whole simulation. However, in our new approach the management can also influence the organizational persistence (by varying the value B). The arrows in Figure 4.18 indicate how the two parameters, the Up and Down Barrier and the value B, affect the *Net Liquidation Value* and the *organizational persistence* within the simulation.

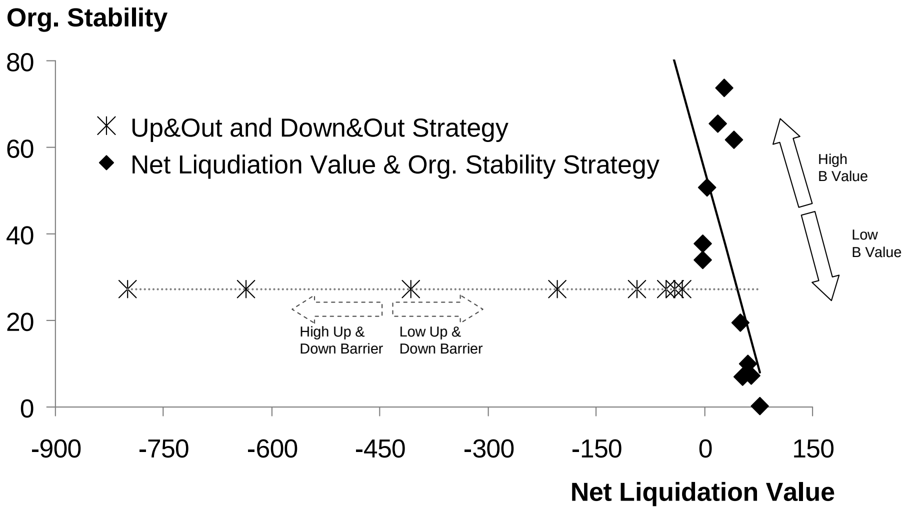


Figure 4.18: Comparison of the results of the two models on a *Net Liquidation Value* & *organizational stability* coordinate system

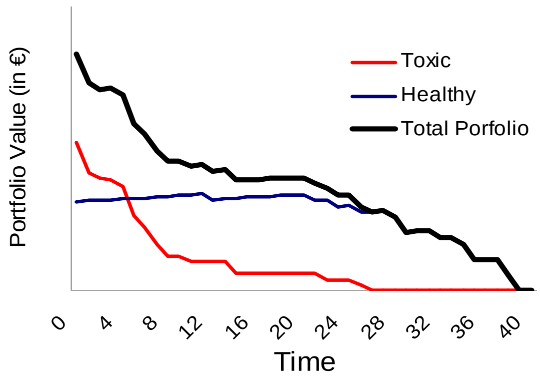
The stars in the graphic depict the results of the Up&Out and Down&Out Strategy, whereas the diamonds are the simulation results of our new model considering the *Net Liquidation Value* and *organizational stability*. The lines are linear regression lines for both models. The arrows indicate how the management could change the focus of the asset liquidation process by setting the two parameters, the Up and Down Barrier and value B.

Considering the sequence of asset liquidation, Figure 4.19 shows that the Up&Out and Down&Out Strategy provokes, compared to our new model, a later selling of toxic assets and an earlier liquidation of well-performing asset. The later selling is caused by the fact, that at the beginning of the liquidation sequence the upper- or lower-barrier is not hit and, thus, the asset are not sold. Consequently, even though an organisation observes a negative development, in this strategy it has to wait to sell the asset until a barrier hit occurs. This is the reason for the worse overall performance of the Up&Out and Down&Out Strategy.

Figure 4.19: Portfolio-Liquidation over time – New Model vs. Current Best Practice

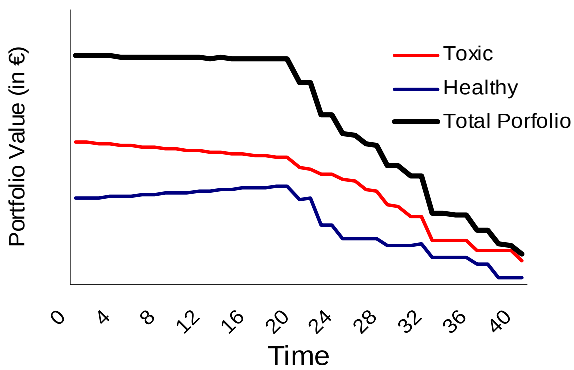
Panel A depicts the results without our optimization model, and Panel B shows the results when asset liquidation and *organizational stability* are optimized together. In Panel B, we see that due to the fact that the barrier is not hit, the asset execution starts later than in Panel A. A barrier hit in Panel B occurs if the asset price process exceeds the barrier of 120% of the initial value or falls below the barrier of 80% of the initial value.

Panel A: New Model - *Net Liquidation Value* & Org. Persistence



Panel B: Portfolio Liquidation over time according to the Up&Out and Down&Out Strategy

- Current best Practice



(ii) Macroeconomic view: For the whole economy, our model, if used by a significant number of organizations, would not only smooth the leaves of employees in a restructuring process (in our case the sale of toxic and well-performing assets) but should consequently also lower the amount of unemployed people in the same region having the same qualifications and specializations. By the principles of supply and demand in the job-market, this means that these people should find quicker a place to work at and, thus, are (on average) unemployed for a shorter period of time. This reduction of unemployed people has a positive effect on the state spending on unemployment compensation and, thus, lowers the cost of a crisis for the whole economy. As a consequence, any state would be wisely consulted to ask – for example in a restructuring plan within the framework of a State Aid Process – for a smooth restructuring of assets and labour in order to lower the costs for the tax payer.

4.6 Summary

In this dissertation we develop a model to consider asset liquidation and organizational restructuring *simultaneously*. An optimization algorithm is derived that solves the problem of asset- and its linked employee-restructuring. Within this algorithm a firm's management can vary a parameter that indicates the importance of asset liquidation versus *organizational stability*. Based on this parameter the new optimization approach calculates the optimal solution.

The combination of asset liquidation *and* organizational restructuring is not only an interesting aspects to the optimal asset liquidation literature but is of great practical importance, especially after the financial crisis. We further show that the combined focus on asset liquidation and organizational restructuring has a positive influence on both and should thus be considered together.

Even though the combination of these two fields of research has not yet been discussed in the scientific literature, this topic will be needed by any organization that has to restructure its assets and organization at the same time. As we have seen from serval discussions with decision makers in the European banking sector, restructuring (assets and employees) is currently a hot topic for almost every bank as a consequence of the financial crisis. Especially for banks that need to submit a viability report or restructuring plan to the European

Commission within the State Aid Process, this model answers the question for the most efficient asset restructuring within a fixed given timeframe. Furthermore, particularly within EU-restructurings, the model also incorporates the difference between the liquidation of toxic and well-performing assets (such as compensatory measures that are required for an approval by the EU).

Chapter -Appendix: Notation Overview

b ...	Focus parameter allows to switch the focus between *Net Liquidation Value* and *organizational stability*
C ...	Stretching parameter regulates the smoothness of the liquidation process
c_i ...	Costs for employee (wage) that manages asset class *i*
d ...	Down step in the Random Walk Process
$\hat{f}_i(x)$ ...	Communication density function
$\tilde{f}_i(x,\lambda_i)$ ...	Leave density function with coefficient λ_i that links the density function to the expected return of the asset class *i*
$f_i^{0\rightarrow}$ ...	Density function for the liquidation of toxic assets
$f_i^{\leftarrow T}$ ...	Density function for the liquidation of well-performing assets
FTE …	*F*ull *T*erm *E*quivalent, i.e. employee
G(.) ...	Net Liquidation Value function
g(.) ...	Permanent price impact function with slope γ
h(.) ...	Temporary price impact function with slope η
I ...	Amount of different asset classes with index *i*
$l_i^{0\rightarrow}(.)$ ...	Density function of the duration that the toxic asset class *i* will be sold and em ployee *i* leaves the company. It is calculated as the convolution ($\circ$) of $f_i^{0\rightarrow}(x,t_i^{0\rightarrow})\circ\hat{f}_i(x)\circ\tilde{f}_i(x,\lambda_i)$
$l_i^{\leftarrow T}(.)$ ...	Density function of the duration that the well-performing asset class *i* will be sold and employee *i* leaves the company. It is calculated as the convolu tion ($\circ$) of $f_i^{\leftarrow T}(x,t_i^{\leftarrow T})\circ\hat{f}_i(x)\circ\tilde{f}_i(x,\lambda_i)$
$L^{0\rightarrow}$ ...	Sum of the convolution of all toxic assets that can be separated into an asset-term $\overline{f_{Asset}^{0\rightarrow}}$ and a FTE-term $\overline{f_{FTE}^{0\rightarrow}}$
$L^{\leftarrow T}$ ...	Sum of the convolution of all well-performing assets that can be separated into an asset-term $\overline{f_{Asset}^{\leftarrow T}}$ and a FTE-term $\overline{f_{FTE}^{\leftarrow T}}$
L ...	Sum of $L^{0\rightarrow}$ and $L^{\leftarrow T}$
m_t ...	Regime in the Markov Switching Model
$n_{t,i}$ ...	Trades of asset class *i* in period *t*. Equals the increments of the trading strategy

$P_{a,b}$ ... Probability for switching from regime *a* into regime *b*

$r_{t,i}$ ... Return of asset class *i* in period *t*. Equals the increments of the price process $s_{t,i}$

$s_{t,i}$ ... Price of asset class *i* in period *t* with drift μ_i and volatility σ_i

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

$t_i^{0\rightarrow}$ ... Toxic asset start selling at $t = 0$ and finish at $t = t_i^{0\rightarrow}$ with an expected value of $\overline{t^{0\rightarrow}}$

$t_i^{\leftarrow T}$ ... Well-performing asset start selling at $t = T\text{-}t_i^{\leftarrow T}$ and finish at $t = T$ with an expected value of $\overline{t^{\leftarrow T}}$

$U(.)$ ... Utility function that links the *net liquidation value* and the *organisational sta bility*

u ... Up step in the Random Walk Process

$X_{t,i}$ ... Trading strategy. Amount of assets of asset class *i* are plans to hold at time *t*

$\overline{Z}_i$ ... Upper barrier for the Up&Out and Down&Out strategy (best practice) with hitting time $\bar{t}_Z$ of price process

$\underline{Z}_i$ ... Lower barrier for the Up&Out and Down&Out strategy (best practice) with hitting time $\underline{t}_Z$ of price process

5 Concluding Remarks and Recommendations

In the aftermath of the financial crisis and in the middle of the proximately followed public debt crisis, it becomes apparent that the financial industry is in the beginning of massive changes in order to restore the financial and, consequently, economic stability. The belief that increasing financial activities and risk transmission only lead to a higher economic efficiency and stability must be rejected. On one hand, financial activities (such as financing businesses) can certainly increase economic growth, but on the other hand fostering high leverage ratios and risk transmission of corporations and states can amplify downturns. Implementing a new paradigm in finance induces a need for new mechanisms. Appropriate mechanisms should recalibrate the interactions in finance such that by focusing on its own profit market participants act in the means of the financial system.

In this dissertation I consider three detailed research questions and propose mechanisms that conduce financial and economic stability. Besides the detailed explanations of results in sections 2-4, I herewith conclude the key findings and derive suggestions (for e.g. regulators or governments) of the three research questions:

(i) How to reduce systemic risk in banking?

Based on the analysis of the main drivers of systemic risk, I elaborate a new soft-bail-out mechanism that reduces the probability of default of financial systems, lowers the bail-out costs, and decreases the bail-out cost volatility. The new proposed concept is financed by the banking industry and penalizes high interlinkages with a new bank tax approache.

According to my results, I drive three recommendations (for regulators and governments):

→ 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.

→ Bank taxes should be related to the interconnectivity of the corresponding banks, as this parameter tends to be the main driver of financial instability.

→ 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 easier to recover on their own.

(ii) How to diminish the risk appetite of banks?

Caused by the quasi bail-out guarantee of states for troubled too-big-to-fail banks, managers of these banks tend to take high amounts of risk. In order to prevent this high risk appetite, I consider the performance related manager remuneration as long call option on the firm profit and the bank bail-outs as long put option on the firm value. Upon this consideration, I have created a hedging mechanism that partly cancels the manager´s risk appetite. I have put forward the idea to use state-issued long put option that need to be implemented in the firm value payoff-structure. Applying this concept in practice could decrease the risk-taking incentives for managers, enhance the expected bank profit, and lower the volatility of the firm value.

The thereof derived recommendations (for regulators and governments) are:

→ Skim the bonus payments of managers.

→ Ask the banks for funding cost payback, as banks with a quasi-bail-out guarantee are benefiting from it in the funding market.

→ These two additional monetary resources should be taken to pay the price of a long put option issued by the state to hedge the risk appetite.

(iii) How to restructure assets and employees?

As a consequence of any crisis organizations have to restructure their activities and assets. In this dissertation, I elaborate a mechanism that optimizes the costs of asset liquidation and the organizational risk of restructuring at the same time.

This consideration of restructuring processes leads to the following recommendations (for regulators, governments, and bank managements):

→ Asset liquidation always comes along with employee reduction

→ Restructuring without the consideration of organizational stability can lead to a clustering of employee leaves, i.e. a too-quick employee restructuring can cause a loss of important knowledge and organizational restructuring risks.

→ Considering both, the asset and employee restructuring, at the same time can optimize execution costs and organizational risk.

I hope that my findings lay the foundation to further research on regulatory mechanism and incentive framework that contribute to restore financial stability.

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Dipl.-Ing. Mag. Bernhard KRONFELLNER

Address: Schottenfeldgasse 66/34, 1070 Wien, Austria

Mobil: +43/676/5797379

E-Mail: kronfellner.bernhard@bcg.com

Webpage: www.kronfellner.at.tf

Birth: 22. 09. 1982

Professional Experience

05.2007-? **The Boston Consulting Group (EUROPE)**
Consultant with leadership experience within the project. Member of the Financial Service Group. Specialised in risk management, treasury, M&A. Additional responsibilities: recruiting key account for the TU Wien

05.2006-10.2006 **JPMorgan (LONDON)**
Quantitative structurer in Equity Derivative Structuring Group: Pricing and structuring of new OTC- and retail structured products with Monte Carlo and programming new OTC-structures.

02.2006-03.2006 **PricewaterhouseCoopers (VIENNA)**
Internship as a financial engineer in the Financial Service Advisory department, where I was dealing with the pricing-methods of derivatives in the framework of IAS 39 and Basel II-implementation

07.2005-08.2005 **EPICON Investment (VIENNA)**
Internship as a financial engineer in the Asset Management division: development and implementation of new VaR-model and a hedging strategy for mutual funds

03.2005 **MARKANT Trading Organisation Far Eastern (HONG KONG)**
Project collaborator in the quality-assurance department: statistics and AQL-quantification-model

09.2004-12.2004 **Groupe Le Duff (PARIS)**
Development of a marketing strategy for the French market in collaboration with the Marketing Department of the Université Dauphine

05.2001-06.2003 **Financial counselling at Objektive Vermögensberatung (WR. NEUSTADT)**
Part-time as well as a full-time employee at one of the biggest financial counselling firms in Austria. Obtained the official exam for the "Austrian Certificate of State for Authorized Financial Consultants"

Education

Vienna University of Technology

03.2009-? Finance & Mathematics (external PhD-Student) at the Department of Finance & Corporate Control
PhD-Study is fully financed by The Boston Consulting Group

10.2002-03.2007 Technical Mathematics – Specialization in Business Mathematics
(Austrian Diplom Ingenieur; Bachelor-& Master-level) finished one semster ahead of schedule

Vienna University of Economics & Business Administration

10.2009-01.2011 Business and Economics (Austrian Magister) – Specialization in Management Science

10.2002-04.2007 Business and Economics (Bachelor-equivalent)

08.2005-01.2006 **City University New York**
Second exchange semester: taking specialised PhD-classes at the Graduate Center New York and MSc-courses at City College New York. Full scholarship from the Joint Study program

08.2004-2.2005 **Université Paris Dauphine**
First exchange semester at the reference of Professor W. Schachermayer and the university supervisors R.Mlitz. Full scholarship from the Erasmus program

09.1993-5.2001 **High School: "BRG Wiener Neustadt"**
A-level examination as well as all other classes passed with distinction

Scientific Contribution

11.2011	Aussenegg, W./ Kronfellner, B.: ***"The Effect of Asset Liquidation for (Bad) Banks´ Stability in the Financial Markets"***, Submitted Paper
10.2011	Aussenegg, W./ Kronfellner, B.: ***"Soft-Bail-Out of Financial Institutions to Reduce Contagion in Financial Systems"***, Submitted Paper
06.2011	Aussenegg, W./ Kronfellner, B.: ***"Restoring the Financial Stability with Mechanism Design"***, Submitted Paper
08.2008	Kronfellner, B.: ***"Prognostizierbarkeit von Finanzzeitreihen: Stochastische Analyse von Marktanomalien und Entwicklung einer Hedgefonds-Strategie"***, VDM-Verlag, 132 p, ISBN: 3836480727
11.2006	Aussenegg, W./ Kronfellner, B.: ***"Analyse zur Prognostizierbarkeit von Finanzzeitreihen"***, Master Thesis

Other Qualifications and Interests

Languages

German	Native speaker
French	Fluent (exchange semester in France, all exams in French)
English	Fluent (professional work experience in the UK, exchange semester in the US)

IT-Knowledge

C, Matlab, SPSS/PASW, Derive, Delphi, Flash, HTML, JavaScript, Arena, Eviews, VBA, Crystal Ball
MS-Office: Word, Excel, Access, Power Point

Self-Advancement

2010	Invitation to and participation at the Forum Alpbach
2009	Ascent of the highest mountain in Austria (Großglocker: 3.798m)
2006	Invitation to a McKinsey Weekend-Workshop in Kitzbühel
2004-2005	Staff member at the Uni Management Club and responsible for the Technical University
2003-2005	Active member at the table tennis Club at the Business University
2001- 2002	Military service (Tank Division)
1999-2000	Headboy of my High School (in charge of the complete organisation of the high school's prom which produced a turnover of approximately € 40.000)
1989-2003	National champion (1995) in table tennis and member of the junior national team