Bank Regulation - The Leverage Ratio Requirement from the Perspective of Stabilizing the Financial System

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List of Abbreviations

AR(1)	First-order Autocorrelation
BCBS	Basel Committee on Banking Supervision
DD	Distance to Default
DS	Datastream
EBA	European Banking Authority
FGLS	Feasible Generalized Least Squares
GCB	German Central Bank
GLS	Generalized Least Squares
IFRS	International Financial Reporting Standards
ISIN	International Securities Identification Number
LCR	Liquidity Coverage Ratio
LR	Leverage Ratio
NSFR	Net Stable Funding Ratio
OLS	Ordinary Least Squares
PCSE	Panel-corrected Standard Errors
PD	Probability of Default
SIFIs	Systemically Important Financial Institutions
SoFFin	Financial Market Stabilization Fund
Std. Dev.	Standard Deviation
US GAAP	United States Generally Accepted Accounting Principles
VIF	Variance Inflation Factor

Chapter 1

Introduction

The recent global financial crisis raises fundamental questions about the objectives and conceptual foundation of international regulation of financial institutions. Increasing vulnerability at individual bank level, and the build-up of system-wide risk led to destabilizing the global economy. Policy makers and banking supervisors question existing approaches to financial regulation and discuss a presumably systemic failure of the international regulatory framework which is proposed by the Basel Committee on Banking Supervision (BCBS). The BCBS develops banking supervision standards and guidelines. The aim is to enhance the understanding of key supervisory issues and to improve the quality of banking supervision at world level. The Committee was first established in 1974 by the central bank governors of the G10 countries[1]. Over the years, bank regulation has undergone continuous development. The collapse of German Bankhaus Herstatt in Cologne was quite spectacular in June 1974 and induced the central bank governors to propose their first recommendations on capital requirements of financial institutions in 1988. This capital accord,

[1] The G10 countries are made up of 11 industrial countries: Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom and the United States. See e.g. Bank for International Settlements (2013b) for details.

dubbed Basel I, was aimed at strengthening capital adequacy of significant banks worldwide. The BCBS recast the first Basel Accord in 1999 by publishing three consultation papers and, finally, adopted the second regulatory framework, Basel II, in 2004. The financial crisis in 2008 encouraged the BCBS to rethink the objectives of their recommendations and how to best meet them. It has been shown that bank regulation is still lagging behind and hindsight is easier than foresight. To address the market failures revealed by the recent crisis and to reinforce financial stability in the global banking system, fundamental reforms to the regulatory framework Basel II were introduced and the BCBS published its third Capital Accord, Basel III.[2] Primarily capital and liquidity requirements for financial institutions were amended. In addition to the already existing but developing recommendations, two new key elements were introduced: a non-risk based Leverage Ratio (LR) and Capital Buffers. Introducing a non-risk weighted requirement as a supplementary measure to the risk-sensitive capital requirements, can help to reduce the incentive for financial institutions to understate risk or to stock up on sovereign debt issued by European countries experiencing economic stress. The latter is an unintended consequence of the Basel III implementation into the European Union law. Generally, banks assign capital depending on how risky their sovereign debt is. Banks in the Euro-zone, however, have a workaround. The debt issued by Member State's central governments, and central banks have a 0% risk weight.[3] In addition, the non-risk weighted LR intends to constrain the build-up to excessive leverage in the banking sector, which helps to maintain and enhance the stability of the financial system. However, some academic researchers and practitioners disagree with the BCBS. Calls are beginning to be made that introducing the LR as a binding constraint has a number of side effects. Decreasing loan volumes and increasing

[2] Details on Basel I, Basel II and Basel III are given in Basel Committee (1988), Basel Committee (2006) and Basel Committee (2009) respectively.

[3] This topic is taken up again in Section 2.2.

loan interest rates are the two most debated ones among researchers and practitioners. These undesirable incentives created by this measure are supposably not in accordance with the objective pursued by the BCBS. More likely, they could cause substantial financial damages which would end in a destabilized banking sector, as shown in Stiglitz and Weiss (1981). Their model illustrates the effects of higher loan interest rates on the riskiness of the pool of loans. Thus, it is up for discussion if this non-risk based measure will actually help to prevent the next global financial crisis by stabilizing individual financial institutions or will entail significant negative economic impact, leading to a destabilizing and vulnerable banking system. This thesis suggests, that a LR requirement may have the unintended consequences of increasing risk in the financial system rather than reducing it. The framework of Stiglitz and Weiss (1981) will be central to the line of argumentation.

To sum up, the global financial crisis has motivated a large number of academic researchers to examine existing and evolving regulatory issues related to financial distress. So far, there is a rich literature on Basel I and Basel II. This thesis picks up the threads of discussion concerning the proposed non-risk weighted regulatory recommendation by the BCBS and tries to drive them forward. The main issue is to analyze the uses of the new key element, the LR, and its side effects from the perspective of maintaining and enhancing financial stability. Still, theoretical and empirical analysis regarding this non-risk based measure is limited. This thesis provides the following contributions:

An introduction to fundamental concepts of financial intermediation, bank regulation and financial stability is provided in Chapter 2. Further, this chapter contains a brief literature review on research being done on the regulatory framework Basel III and the financial soundness measures subsequently used in Chapters 3 and 4. First of all, Chapter 3 considers theoretical underpinnings of both the regulatory and financial stability measures. Then, an empirical investigation to analyze the capitalization of the banking sector and its financial risk is provided. Finally, results of the financial risk analysis are discussed. In order to address the research question, a panel data regression model, which investigates the nexus between the LR and financial stability and its reasons, is proposed in Chapter 4. First, the empirical methodology and hypotheses are developed. Then, the regression model is estimated and the performance of descriptive statistics and regression diagnostics is presented. Presentation of findings regarding the panel data analysis and detailed discussion follows. Finally, robustness of the regression results is investigated. Chapter 5 concludes.

Chapter 2

Background Theory and Literature Review

Before entering the analysis in the following chapter, it is relevant to understand why financial intermediaries exist. A review on the contemporary theory of financial intermediation can give a clear answer and puts the subject into the right context. Further, a common understanding of bank regulation and financial stability is essential to delve deeper into this thesis. Bank regulation is constantly adapted and revised by banking supervisors. This fact can be explained by the permanently increasing complexity of the global financial system and the occurrence of financial crises from time to time. Furthermore, financial stability is a broad term and can be expressed in several ways. Every regulatory and stability concept recently discussed in literature cannot be reviewed in this introductory chapter. However, the relevant regulatory framework for this thesis and the selected measures to signal financial fragility are described in this chapter.

The purpose of the second chapter is to provide an overview of financial intermediation and to establish a common understanding of the terms bank regulation and financial stability. The chapter is structured as follows: Section 2.1 illustrates, first of all, the functions and the role of financial intermediaries, and secondly, the reasons for the existence of financial intermediaries. In Section 2.2 the key elements of the third Basel Accord are presented before putting the focus on the LR requirement. Then, the term 'financial stability' is defined by introducing two dimensions of system stability and two proxies to measure financial soundness. In Section 2.3, a brief literature review is presented. Firstly, recent academic literature in the area of bank regulation, more precisely, Basel III, and secondly, academic research done on the introduced financial stability measures is summarized.

2.1 Financial Intermediation

"Banks" are not the only institutions which offer a variety of financial products. Hartmann-Wendels et al. (2010) discuss at length what a bank is, and what banks do. Often banks compete against other institutions, such as the capital market or insurances. Banking operations may be complex and varied, but before giving a definition of a bank, a closer look at its main function is illustrated. The simplest way of describing a bank is to study the allocation of funds between economic agents, or more precisely, to study the borrower-lender relationship. Some agents are in financial surplus and others in financial deficit. The former, called lenders, wish to profitably invest their funds, whereas the latter, referred to as borrowers, require to obtain outside finance in order to operate profitable investment projects. However, there are several factors which complicate the efficiency of performing the allocation of funds between those agents. The agents' attitudes towards risk, or the level of information regarding the contracting situation, are probably the most important ones. Thus, the central question is how supply and demand of capital can be balanced. The formation and development of markets is the answer to this question. In economics, a market refers as to an aggregate of sellers and buyers of a certain good, or service, and the transaction between them. A financial market is a market place where financial contracts, such as equities, bonds, derivatives, or currencies, are traded. Freixas and Rochet (2008) argue that for centuries, banks alone essentially performed the economic function of the financial system. Financial markets have developed dramatically over the last 50 years. As a result, financial markets and banks are now providing nearly the same services while banks used to offer some exclusively. As opposed to capital markets, a bank is an institution who finances a significant fraction of their loans through the deposits of the public by granting loans and receiving deposits from the public. Such intermediaries between capital supply and demand are called financial intermediaries. The bank is a financial intermediary in the narrow perspective while rating agencies, a broker or a dealer are financial intermediaries in the broader perspective[1].

This section, first of all, illustrates the basic functions and the fundamental role of financial intermediaries, and finally, discusses various sets of explanations of their existence. Dewatripont et al. (1994) and Freixas and Rochet (2008) contributions formalized the emergence of financial intermediaries while Bhattacharya and Thakor (1993) and Santomero (1984) provided two major reviews of contemporary financial intermediation theory which has been discussed in the existing intermediation literature of the past two decades.

2.1.1 The Functions of Financial Intermediaries

Examining the basic functions which financial intermediaries perform, helps to provide a better understanding of how financial intermediation improves the allocation of capital. Not every bank has to perform each of the following

[1] Further details are given in Section 2.1.2.

functions. For instance, universal banks do perform all of these functions, but specialized banks do not need to. As discussed by Freixas and Rochet (2008) and Merton and Bodie (1995), contemporary banking theory classifies these functions into four main categories:

1. Offering liquidity and payment services
2. Managing risk
3. Monitoring borrowers and processing information
4. Transforming assets

First of all, a financial intermediary offers liquidity by providing borrowers with access to capital and providing liquidity to investors. Assets are assumed to be inherently illiquid while liabilities are much more liquid. Banks create liquidity by offering claims with higher short-term returns for given long-term returns. The amount of liquidity, though, is influenced by the liquidity in the financial markets. In addition, a financial intermediary provides ways of settling and clearing payments to facilitate the exchange of goods, assets, and services. Banks can serve this function with wire checking accounts, transfers, and credit, or cash cards. These mechanisms for securities transactions are designed to deal with the risks and the costs, such as processing fees, associated with the process. Risk may arise due to the fact that one party may not fulfill its terms. For instance, the borrower does not repay its loan, or the lender fails to deliver.

The second function of financial intermediaries is to manage risks. Ways to manage uncertainty and to control risks are provided. Freixas and Rochet (2008) define four sources of risk: credit risk, interest rate risk, liquidity risk, and off-balance sheet operations. Particularly, the latter has been soaring in the last decades. Credit risk, historically, was small. Still, bankers tried to make their loan secure through, for example, collateral. Through time the riskiness of loans seems to have increased. This change in credit risk can be traced back to the start of investment banking which can be seen as a different concept from traditional credit activity. Investment banks have a different philosophy of banking because it involves advancing money to the industry rather than being a simple lender who gets good guarantees. This implies making more risky investments and buying stocks. However, this appraisal of risk on a loan is one of the main functions of bankers. In addition, Diamond and Dybvig (1983) argue that the asset transformation function has implications for the management of risks. For instance, when issuing liquid deposits guaranteed by illiquid loans or transforming maturities, a bank takes market risks (interest rate risk and liquidity risk). These risk may arise when the cost of funds, which depends on the level of short-term interest rates, rises above the interest income which is determined by the interest rates of the loans granted by a bank. The bank may face unexpected withdrawals, even though they pay no interest on deposits. This results in seeking more expensive sources of funds. The financial intermediary will have to manage the combination of these two market risks in order to balance the difference in maturity and the one in the marketability of the claims held and that of the claims issued. The increasing involvement of financial intermediaries in financial markets implies that they are more and more subject to market risk. Furthermore, off-balance sheet operations can be defined as loan commitments, credit lines, and guarantees that do not correspond to a genuine liability or asset for the bank but only to a conditional commitment. Banks sell and buy risky assets, weather or not they are reported on the balance sheets. Thus, banks may want to manage this risk, for example, by hedging their risks.

The third function of financial intermediaries discussed by Freixas and Rochet (2008), is monitoring and information processing. Diamond (1984) also argues that due to problems resulting from imperfect information on borrowers, it is necessary to invest in the technologies that permit financial intermediaries to screen loan applicants and to monitor their project. This function implies that financial intermediaries and firms develop long-term relationships which help to mitigate the effects of moral hazard. This can be seen as one of the main differences between issuing securities and bank lending in financial markets. Bond prices are assumed to reflect market information whereas the value of a bank loan results from this long-term relationship which implies that the value is prior unknown to the market and to the regulator. Thus, Merton (1992) refers to bank loans as being opaque. In this context, financial intermediaries provide price information useful for decision-making in various sectors of the economy.

Finally, three functions of transforming assets are being discussed by Freixas and Rochet (2008) and Merton and Bodie (1995): convenience of denomination, risk transformation, and maturity transformation. The former refers to the fact that a bank chooses the unit size of its products in a way that is convenient for clients. Financial products are either desired by investors or issued by a firm. Often small deposits face large investors willing to borrow indivisible amounts. Traditionally, this viewpoint of asset transformation is seen as the main justification of financial intermediation. The link between the financial products, deposits and loans, can be provided by this function of asset transformation. For instance, a bank performs the transformation of large-denomination financial assets into smaller units or collects small deposits in order to invest the proceeds into large loans. Risk transformation is the process whereby financial intermediaries can spread the risks of lending by having various borrowers. Financial intermediaries are willing to risk that some borrower is not paying back the loan because they lend capital to a large number of borrowers. The eventual loss can be absorbed due to the charged interest rate on all other loans. In addition, risk transformation occurs when the risk-return characteristics of bank deposits are better than the ones of direct investments. This scenario may occur when indivisibilities in the investment arise, in which case a small investor cannot diversify its portfolio. Maturity transformation is the transformation of securities with short maturities, offered to depositors, into securities with long maturities, which are desired by borrowers. In general, borrowers need capital for long periods of time and many depositors want to be able to withdraw their deposits at short notice or on demand. If people rely on borrowing directly from the lenders there would be a problem: the lender would probably not be prepared to lend for a long enough period. The financial intermediary borrows capital from a vast number of small depositors which are able to withdraw at short notice, and lends for a long period of time. Thus, financial intermediaries lend for longer periods of time than they borrow. This function necessarily implies a risk. Given the depositor's claim, the banks' assets will be illiquid. However, this risk can be limited due to interbank lending or derivative financial instruments available to banks.

Next, a common understanding of the role of financial intermediation and why financial intermediaries exist is presented.

2.1.2 Explanations for the Emergence of Financial Intermediaries

Although this thesis is specifically focused on banks, this subsection adopts a broader perspective and studies financial intermediaries in general, as illustrated in Freixas and Rochet (2008). This perspective includes an economic agent, broker and dealer which are clear examples of intermediaries in the financial sector. The economic agent specializes in the activity of buying and selling financial claims. This notion of intermediary is analogous to a retailer in the theory of industrial organization where an agent buys goods or services from producers and sells them to final customers. Broker and dealers operate on financial markets, and thus belong to the financial intermediaries in the broader sense. A bank can be seen as a retailer of financial securities. Securities issued by borrowers are bought, i.e. banks grant loans, and these securities are sold to lenders, i.e. a bank collects deposits. Banking activity though is considered to be more complex. Banks deal with financial contracts rather than with financial securities. The difference is that contracts cannot be easily resold whereas securities are anonymous and thus easily marketable. As opposed to other financial intermediaries, banks must hold these contracts in their balance sheets until they expire. In addition, banks transform financial contracts and securities because the characteristics of borrowers' contracts are usually different from the ones of depositors, as seen in the previous section.

The objective of the theories of financial intermediation is to explain the emergence of intermediaries by means of a model. In general, first of all, a market, where financial contracts are dealt, is modeled. Then, it is shown that the utility for all individuals in the market increases by the existence of a financial intermediary. Note that in the ideal world of frictionless and complete financial markets, financial intermediation is of no importance. Campbel and Kracaw (1980) argue that in a market environment with perfect information, financial intermediaries could perform no unique service that investors are unable to reproduce as easily. Investors and borrowers obtain optimal risk sharing and would be able to diversify perfectly. As soon as indivisibilities and nonconvexities in transaction technologies are introduced, perfect diversification is no longer feasible. Thus, it has long been understood, that financial intermediation is to be developed as a response to market imperfections. The foundation for understanding the existence of financial intermediaries is traditionally provided by transaction costs and asymmetric information. Hellwig (1992), amongst others, argues that the transaction cost approach does not in fact contradict the assumption of complete markets in the neoclassical theory. In a market with no financial intermediary, transaction costs hamper individuals to obtain a optimal diversification. To undertake a large number of coalitions between investors and borrowers, will be inefficient due to transaction costs. Financial intermediaries can be seen as coalitions of individual borrowers and lenders who exploit both, economies of scope and economies of scale in the transaction technology. As a result, the number of coalitions between investors and borrowers is minimized and individuals obtain almost perfect diversification.

The second approach derives from the neo-institutional perspective. Asymmetric information are central to the foundation of these theories. Market imperfections due to asymmetric information can be seen as a specific transaction cost. Hartmann-Wendels et al. (2010) and Thakor and Boot (2008) explain the different types of asymmetric information. The informational asymmetries differ according to the timing in which the asymmetry takes place. In general, literature distinguishes between three basic types: adverse selection, moral hazard, and costly state verification. Adverse selection asymmetry arises when the information is asymmetric even before the contract is signed. One party in a transaction knows something about its own characteristic that the other party does not know. This asymmetry is often referred to as a hidden information problem in a market, where, for example, sellers may know more about a product than the customers. This asymmetry was first pioneered by Akerlof (1970) who examined the markets for used motor vehicles. Applied to the borrower-lender relationship, the borrower could lie about his individual risk. Low risk borrowers are more likely to have a higher probability of repaying a loan. Due to the lack of information, a bank cannot identify "good" borrowers. Thus, this asymmetry can provoke that bank offers attract an adversely biased selection of applicants. Moral hazard implies that the information is symmetric before the contract between lender and borrower is accepted but asymmetric afterward. Two cases can be classified: hidden action and ex post hidden information. The former is characterized by a non verifiable action carried out by the borrower after the signature of the contract. For instance, the borrower could change his investment choice by investing in a different project which is not beneficial or profitable for the lender. The latter implies that the borrower will know more than the lender about an important variable once the contract is accepted. Thus, actions undertaken by the borrower are not directly observable by other parties, nor perfectly inferred by observing the outcomes. Moral hazard results in temptations for shirking, or carelessness by borrowers, and increases the probability of undesired outcomes for one party, in this case the lender, post contractual. Costly state verification is characterized by the care about end-period-wealth. Information is asymmetric in the sense of that the performance of an investment project may be observed at no cost only by the borrower, while it can be observed by the lender only after paying a state-dependent verification cost. Thus, the verification of the performance is costly to the lender. In addition, the costly state verification problem gives the borrower the incentive to lie about the investment project's performance in order to lower the repayment amount to the lender.

Various theories which attempt to explain the existence of intermediaries in capital markets have been offered. In the following, selected explanations for the emergence of financial intermediaries which place the emphasis on lending business transactions, are presented. With regard to the following analysis in this thesis, the theories of financial intermediation which focus on the deposit business transactions, are neglected[2]. Due to the increasing complexity of the models, each theory focuses on very few market imperfections and neglects all others. In this context, the theories distinguish between transaction costs and informational asymmetries as a reason for the existence of financial intermediaries. Table 2.1 summarizes the theories which are discussed next.

Foundation of theories		Paper
Transaction costs		Benston and Smith (1976)
Informational asymmetries	ex ante	Leland and Pyle (1977)
		Ramakrishnan and Thakor (1984)
	interim	Thadden (1995)
	ex post	Diamond (1984)
		Williamson (1986)

Table 2.1: The traditional theories of financial intermediation

Benston and Smith (1976) made an effort to provide an explanation of the purpose of intermediaries, assuming a model with an imperfect market approach which relied on transaction costs. Their work shows that the analysis of transaction costs is central to the motivation of the intermediary function. Financial intermediaries create financial commodities whenever it is assumed that these commodities can be sold for prices which are expected to cover the direct costs and opportunity costs. By acquiring financial commodities, a consumer's consumption decision can be affected in the way that inter-temporal and intra-temporal transfers of consumption can be achieved. Individuals derive a higher utility by incurring lower transaction costs. Benston and Smith (1976) argue that several forms of financial intermediation, such as stock exchanges, dealer,

[2]See, amongst others, Diamond and Dybvig (1983). Their model considers banks as coalitions of depositors. Thus, the existence of financial markets impairs the provision of liquidity insurance by deposit banks, i.e. the insurance against liquidity shocks is provided by banks. Demand for this insurance comes from the assumption of risk aversion of depositors in the model.

or banks, try to reduce transaction costs. However, the form which is exemplified by banks has a comparative advantage over, for example, a stock exchange. This intermediary purchases large blocks of securities, packages those in a form that is demanded by some individuals, and finally, sells this package at a price which covers all its transaction costs. Thus, the authors represent with their approach the essential feature of financial intermediation, focusing on transaction costs. Transaction costs can explain the existence of financial intermediation but their magnitude does not appear sufficient to be the only cause in many cases. Therefore, it is suggested by many researchers that informational asymmetries are a more powerful explanation and a primary reason that financial intermediaries exist. Numerous financial markets are characterized by asymmetrically informed lenders and borrowers. Borrowers typically know their industriousness, collateral, and moral rectitude better than lenders do. In general, lenders would benefit from knowing the borrowers' true characteristics. However, information asymmetries, such as adverse selection, moral hazard, and costly state verification, hamper the direct transfer of information between market participants. Financial intermediation is shown to dominate lending and borrowing between individuals.

Given the adverse selection (ex ante) informational asymmetry, Leland and Pyle (1977) and Ramakrishnan and Thakor (1984) work can be viewed as an explanation for the emergence of financial intermediaries. Leland and Pyle (1977) were the first to propose that a financial intermediary is an evaluator of credit risk for the inexperienced depositor by functioning as a filter to interpret signals in a financial environment with imperfect information. The authors argued that a large number of firms is required to gather and sell information about particular classes of assets due to the limited information on the quality of these assets. Nevertheless, two problems hamper these firms which try to sell such information directly to investors, and thus, nonfinancial firm signaling is quite fragile. The first is, that resources that a firm invests in obtaining these information become available to the market as a public good. Accordingly, difficulties to capture the return associated with its value arise. The second problem is that potential users have difficulties in distinguishing good information from bad. If this is the case, the price of information reflects its average quality. While the entry for firms offering poor information quality is easy, firms which expend resources to collect good information leave the market because they receive a value reflecting the average low quality. In this context, the equilibrium will be consistent of only low quality information.[3] These problems can be overcome if an intermediary, which buys and holds assets on the basis of its specialized information, gathers the information. The firm's information is embodied in a private good, the returns from its portfolio. The willingness of the intermediary to dedicate wealth to the firm serves as a signal. It demonstrates that the underlying assets are found to be of sufficient value and the commitment to the portfolio. Ramakrishnan and Thakor (1984) formalized the ideas of Leland and Pyle (1977). They give a further explanation of the emergence of financial intermediation, focusing on diversified information brokers, such as credit bureaus, investment bankers, or accounting firms. These intermediaries perform an intangible service, generating information and are able to lower costs of information production. To see this, imagine that a firm needs to raise capital from a large number of investors. Without an financial intermediary (referred to as an intermediating information broker in the model of Ramakrishnan and Thakor (1984)), information production would be duplicated as each investor wishes to screen the firm. In this context, an intermediary reduces the duplication in information by, for example, certifying the firm's economic worth. Thus, it is concluded, that financial intermediation improves welfare if ex ante

[3] Akerlof (1970) referred to the same problem by using a market for used cars.

informational asymmetries are present in capital market.

Thadden (1995) chose the moral hazard (interim) informational asymmetry to identify reasons for the existence of financial intermediaries. As in Diamond (1984), he argued that information gathering is costly, and thus, there is an incentive to centralize information monitoring in one person's hand, the intermediary. Due to his assumption of interim informational asymmetry, the line of argumentation why financial intermediaries may act as delegated monitors of projects, is different than in Diamond (1984) model. In this model, monitoring can have a positive effect on which project the borrower will be undertaken rather than on the verification of the performance of a project by eliminating the borrower's moral hazard problem with respect to investment choice.

Given the costly state verification (ex post) informational asymmetry, two essential papers developed a theory of financial intermediation: Diamond (1984) and Williamson (1986). Diamond (1984) paper can be seen subsequent to Leland and Pyle (1977). He demonstrated the value of diversification in reducing monitoring costs. In contrast to Ramakrishnan and Thakor (1984), who focused on private information about the projects' ex ante prospects, Diamond (1984) focused on the ex post realized returns. It is assumed that the information, in this case the performance of an investment project, by a given person cannot be observed or monitored without cost by others. Thus, monitoring can be referred to as any activity aimed at preventing opportunistic behavior of the borrower ex post. The theory of financial intermediation is based on reducing these cost of monitoring information. If there are many lenders who invested in a project, the cost of monitoring the data which a borrower observes, may be very high. In this context, monitoring involves increasing returns to scale which implies that this task is more efficiently performed by specialized firms. Therefore, individual lenders tend to delegate the task of costly monitoring to an intermediary instead of performing it themselves. A gross cost advantage in collecting this information can be achieved. In line with the argumentation of Ramakrishnan and Thakor (1984), Diamond (1984) argued that if each lender monitors directly, a duplication of effort will arise. Moreover, a free-rider problem could be the alternative, in which case no lender monitors. However, delegated monitoring introduces a new problem: the provided monitoring information may not be reliable. Therefore, the monitor has to be given incentives to do the job properly. Financial intermediaries can provide solutions to this incentive problem as discussed by Diamond (1984). He suggests that investors can impose non-pecuniary penalties on the financial intermediary who does not perform its monitoring activity well. In addition, the cost of monitoring can be made as small as possible by diversifying the bank's loan portfolio. To sum up, a financial intermediary has a net cost advantage relative to direct borrowing and lending. Williamson (1986) model considered ex post asymmetrically informed borrowers and lenders, as well. Accordingly, the focus is on the return on the borrower's investment project. The lender is able to monitor the output of the projects but monitoring is very costly. As in Diamond (1984), financial intermediaries perform a "delegated monitoring" role and are single agents. In contrast, the authors assume that the lender monitors only in the event of default. It is concluded, that the costly monitoring of lenders and large-scale investment projects imply increasing returns to scale in borrowing and lending. This effect can be exploited by financial intermediaries.

To sum up, in a context of informational asymmetries, financial intermediation is a way to improve efficiency. Whether it is screening projects in a context of ex ante asymmetries, preventing opportunistic behavior of borrowers during the realization of the project, or punishing and monitoring a borrower who does not meet contractual obligations, ex post. Yet, these activities could be performed by the individual lenders themselves or by specialized firms such as rating agencies. However, financial intermediaries have a comparative advantage in these activities: exploiting scale economies by financing many projects, providing funds of several investors to balance the small capacity of investors compared to the size of projects, and reducing the costs of monitoring (the surplus gained from exploiting scale economies has to be more than the costs). Accordingly, they are a response to the incapability of market-mediated mechanisms to efficiently resolve informational asymmetries.

2.1.3 The Stiglitz and Weiss (1981) Model

The next model is not necessarily a traditional theory of the emergence of financial intermediaries but established a link between financial intermediation and equilibrium credit rationing. As this model is central to the line of argumentation in Chapter 4, it is discussed next. Credits are rationed by banks which can be seen as a classic form of market failure. Stiglitz and Weiss (1981) framework, where borrowers and lenders are risk neutral, sought to explain why banks ration credit by focusing on two informational asymmetries: adverse selection and moral hazard. More precisely, their work "*Credit Rationing in Markets with Imperfect Information*" analyzed the effects of higher loan interest rates on the "riskiness" of a bank underlying credit rationing as an equilibrium feature of the loan market. Banks and borrowers seek to maximize profits and the lenders are concerned about the interest rate they receive on a loan and the loan riskiness. The authors illustrated that the level of interest rates a bank charges its borrowers affects the riskiness of its loan portfolio due to the adverse selection effect and the incentive effect. The main finding in their analysis is that a bank's expected return can peak at a "bank-optimal", r^*, loan interest rate due to these two informational asymmetries. The adverse selection effect is a consequence of different quality of borrowers, i.e. different type of borrowers imply different probabilities of repaying the loan which affects the expected return to a bank. Banks cannot distinguish among credit applicants, but would like to be able to identify low risk borrowers who are more likely to repay, in order to maximize their return. Consequently financial institutions need to use screening devices in order to identify the borrower type. The interest rate can be used as such a screening device. A bank assumes that different borrower types are willing to pay different interest rates. High risk borrowers act on the assumption that the probability of repaying the loan is relatively low and are willing to borrow at high interest rates which will possibly lower the bank's profits. Thus, an increase in loan interest rates affects low risk borrowers more adversely than high risk borrowers and drives low risk borrowers out of the market. The authors conclude that an increase in loan interest rates increases the average "riskiness" of a bank's borrowers. To clarify, an example is provided: there are two indistinguishable types of borrowers, a low risk and a high risk borrower, who seek to borrow €1 to invest in a project that will pay a random amount, C, at the end of the period. The maximum interest rate on a loan, r_S^*, that a low risk borrower is willing to pay for a loan satisfies

$$\int_{[1+r_S^*]}^{\infty} [C - \{1 + r_S^*\}] \, dF_s(C) = \mu, \tag{2.1}$$

and the maximum interest rate, r_R^*, that a high risk borrower is willing to pay solves

$$\int_{[1+r_R^*]}^{\infty} [C - \{1 + r_R^*\}] \, dF_R(C) = \mu, \tag{2.2}$$

where $f_S(\cdot) \sim (0, \infty)$ and $F_S(\cdot)$ are the density and cumulative distribution of C, respectively, for the low risk borrower and $f_R(\cdot) \sim (0, \infty)$ and $F_R(\cdot)$ for the high risk borrower. It is assumed that $F_R(\cdot)$ is second-order stochastically dominated by $F_S(\cdot)$ and thus is a mean-preserving spread of $F_S(\cdot)$.[4] Further μ is the expected minimum return of each borrower. The assumption that increasing risk across the borrower types is defined through a sequence of second-order stochastic dominated relationships, i.e. that the distribution function of the low risk borrower involves less risk than the distribution function of the high risk borrower, implies that high risk borrowers are willing to pay a higher interest rate for a loan. It can be followed: $r_R^* > r_S^*$. Under this assumption any increase in interest rates of loans precipitates adverse selection, i.e. low risk borrowers are discouraged by high interest rates and drop out of the market. As a consequence, the credit applicant pool is on average riskier which could lead to a decrease in the bank's expected return. Giving a credit rationing equilibrium, the demand for loans at r^* exceeds the supply of loans at r^*. Any bank that increases its loan interest rate beyond r^*, would lower its expected return. Thus, the bank is unwilling to extend credit to a rationed borrower even if the borrower is willing to pay a higher interest rate. The case of moral hazard works analogously in Stiglitz and Weiss (1981) framework, but now a single borrower is facing multiple investment opportunities. The bank is not able to monitor perfectly and costlessly all the actions of borrowers and take into account the effect of charged interest rates on loans on the behavior of borrowers. The authors show that charging high interest rates increases the attractiveness of riskier projects, i.e. increasing interest rates skew the borrower's project preference toward greater risk. These projects are characterized by higher re-

[4] Stiglitz and Weiss (1981) assume that $F_R(\cdot)$ corresponds to greater risk in the sense of mean preserving spreads, see Rothschild and Stiglitz (1970). It can be followed that projects undertaken by high risk borrowers have a greater variance than projects undertaken by low risk borrowers. However, Rothschild and Stiglitz (1970) argue that, for measuring risk, the mean preserving spread criterion is stronger than the increasing variance criterion. In addition, the authors show that risk-adverse investors prefer the project with the lower variance given two projects with equal means. Note that Stiglitz and Weiss (1981), for simplicity, assume that borrowers and lenders are risk neutral while proving that the interest rate acts as a screening device.

turns in the case of success[5], but lower probability of success which leads to the known effect of lower repayment probabilities. Again, low risk investors who more likely invest in safe projects with modest returns, drop out of the market because the high interest rates will reduce their profit. The authors conclude that the expected return from the undertaken projects to a bank is affected in two ways. In the short run, a direct effect is observable that higher interest rates increase the return to a bank. In the long run, the adverse selection and the incentive effect of interest rates lead to lower bank returns and credit rationing. If an increasing number of high risk projects are undertaken, the riskiness of loans increases and a bank's expected return decreases. At the "bank-optimal" interest rate the expected return is maximized. At this point demand for loans exceeds supply. Due to credit rationing beyond this point supply does not equal demand but loans are riskier and expected returns decrease. Therefore, credit rationing can arise from moral hazard (often referred to as the incentive effect), adverse selection, or both.

Next, a common understanding of the terms bank regulation and financial stability is established.

2.2 Bank Regulation and Financial Stability

The recent global financial crisis showed the vulnerability of the financial system. Taylor (2009) argues that the crisis became acute in August of 2007 where money market interest rates rose dramatically. The situation was worsened in September and October of 2008. A serious credit crunch with large spillovers weakened an economy that was already suffering from the enduring impacts of the housing bust in the US and the oil price boom. In literature, a manifold

[5]Stiglitz and Weiss (1981), p. 396, give theoretical justification that expected profits on the project increase with risk.

reason for the worsening of the crisis was the decision of the US government, not to step in to prevent the insolvency of Lehman Brothers in September 2008[6]. The collapse of this bank may have helped to trigger a banking crisis that swept across the globe. The BCBS argues that excess leverage, capital of insufficient quality and inadequate liquidity buffers led to the build-up of the crisis at individual bank level. A pro-cyclical deleveraging process and the interconnectedness of systematically important financial institutions (SIFIs)[7] were finally responsible for the build-up of system-wide risk. Taylor (2009) affirms that risk in financial institution's balance sheets has been the heart of the crisis from the beginning.

International regulators and policy makers address these vulnerabilities by adopting a new regulatory framework as a reaction to the latest banking crisis. The paper "Strengthening the resilience of the banking sector"[8] by the BCBS is being referred to as Basel III by practitioners. The Basel Committee is located at the Bank for International Settlements. Currently, its members are supervisory authorities of each member state and representatives of the central banks from 27 countries. The BCBS develops recommendations and banking supervision standards. The recommendations by the Committee are non-binding but are adopted by far more countries than the member states. Before giving an in depth description of the Basel III accord[9], the development of this capital framework is illustrated. The first accord, Basel I, was proposed by the BCBS in 1988. After the collapse of the Bankhaus Herstatt, there was concern among the central bank governors that the significant banks throughout the world might have inadequate capital levels. That concern led to recommending comprehen-

[6]See e.g. Basel Committee (2010c).

[7]SIFIs are financial institutions whose disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity, see Basel Committee (2010c).

[8]See Basel Committee (2009).

[9]See Bank for International Settlements (2013a).

sive changes in the requirements for the capital adequacy of credit institutions. Under this capital framework, the liable capital of credit institutions must be equivalent to at least 8% of their weighted risk assets. This measure is designed to cover default risk. The originally simple framework, Basel I, from 1988 was replaced by the Basel II accord in 2004. In 1999 the BCBS published a first consultation paper on the recasting of the capital requirements under Basel I. A second and third consultation paper followed and finally, negotiations ended with the adoption of the new Basel II accord. The main criticism of Basel I was that the accord did not allow for any differentiation in the calculation of the capital requirements for credit risk. The actual risk was frequently not properly captured. Now, it is possible to calculate capital requirements for credit risk in a more risk-sensitive manner due to various procedures for measuring credit risk. Credit institutions are free to use the credit risk standardized approach or the internal ratings-based approach (IRB). The main difference between these two approaches is the assignment of risk-weights. Using the former approach, credit institutions can either apply fixed risk-weightings or credit ratings of recognized rating agencies, whereas institutions which use the IRB can apply own estimates. Thus, the key objective of the Basel II framework is to make the capital requirements take greater account of risk. Other objectives are to create basic principles for qualitative banking (Pillar II) and to impose disclosure requirements (Pillar III). The key elements of the Basel II framework are based upon the three pillars of Basel. The pillars were first introduced under Basel II but still stand under Basel III, and thus are discussed briefly. Decamps et al. (2004) provides an overview. Pillar I aligns the rules for determining the capital requirements and gives a definition of the concept of capital for banking supervision purposes. The capital requirements of Pillar I include credit and market price risks and were extended to operational risks for the first time under Basel

II. Pillar II governs provisions regarding the Supervisory Review Process. This pillar imposes requirements on institutions and national supervisory authorities. Banks are required to assess their overall risk profile in addition to the risk specified under Pillar I. Thus, the key elements are the supervision by supervisory authorities and the establishment of adequate risk management systems. Pillar III contains disclosure requirements that institutions have to meet in order to strengthen market discipline. It is expected that well-informed market participants reward credit institutions that have effective risk management in their lending and investment decisions and punish riskier behavior accordingly. This gives the credit institutions the incentive to control their risks and manage them efficiently. Obviously the implementation of the Basel II accord did not achieve its goal to sustain the stability of the financial sector. Its shortcomings were revealed during the crisis. The traditional regulatory approach, based on capital requirements has come up short in maintaining financial stability. It becomes apparent that banks struggled even though capital requirements were met. It is more likely, that excessive leverage seemed to be the root of the crises. As a response to the ongoing criticism towards Basel II, the Basel Committee revised the accord again, a time-consuming process that led to the new capital and liquidity framework. At the Seoul Summit in November 2010 the G20 leaders endorsed the Basel III Accord, which addresses the weaknesses of the second Basel accord by introducing a number of micro and macro prudential measures. The aim being to promote greater resilience of the global banking system and to contain systemic risk in order to support stable economic growth at any time. The new requirements should preclude financial institutions from taking excessive risks and enable them to withstand future periods of stress without extraordinary government support. The Basel III accord will be translated into national laws and regulations. The implementation was supposed to start on January 1, 2013 and fully phased in by January 1, 2019. Basel III was developed and proposed by the BCBS. The European Commission has drafted its Capital Requirements Directive, "CRD IV", in 2012, to bring the regulatory standards on bank capital adequacy and liquidity of the BCBS via a Regulation and a Directive into European law. On 26 June 2013 the Capital Requirements Regulation and the Capital Requirements Directive were adopted by the European Union and published in the Official Journal of the European Union[10]. Both regulatory frameworks were entered into force on 17 July 2013. Next, the package of the Basel III accord will be illustrated. The following key elements are considered:

1. Improving the quality, quantity and international consistency of the capital base.
2. Introducing a Leverage Ratio as a risk-independent control parameter.
3. Introducing additional capital buffers: Capital Conservation Buffer and Countercyclical Buffer.
4. Introducing a short and long term liquidity ratio: Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR).
5. Improvement of the coverage of counterparty risk.

The focus in this thesis is on the second listed key element of the Basel III Accord, the Leverage Ratio (LR), which has already been adopted by the US in their national law under Pillar II of the Basel II agreement. However, understanding the new definition and requirements of regulatory capital is helpful in order to define the newly introduced non risk-based control parameter. Thus,

[10] Detailed information on the legislative package is provided by the European Union, see European Union (2013a) and European Union (2013b) for the Directive and the Regulation, respectively.

the proposed elements of the Basel III framework, as discussed by Basel Committee (2009), are presented briefly. They can be differentiated into two groups: the risk-based capital requirements which distinguish between different levels of risk, and the non-risk based requirement which disregards such differences. To begin with, the risk-based capital requirements are introduced. First of all, the accord aims at improving the quality of regulatory capital. The Basel Committee raised the quality of capital by putting the focus on Tier 1 capital to absorb losses. Tier 1 capital can be divided in two forms of capital: common equity and additional Tier 1 capital. The criteria for Tier 1 capital are strongly geared. Accordingly, hybrid capital instruments may only be recognized as components of Tier 1 capital to a limited extent and subject to much stricter conditions. The BCBS has set out 14 criteria for common equity which apply to joint stock companies and non-joint stock companies. That the capital instrument represent the most subordinated claim in the event of the institution's liquidation is the most important criteria. Moreover, this instrument is to be transferred for an unlimited period and is only to be repaid in the event of liquidation. Furthermore, at the time of issue, the regulated institution may not promise in its contractual terms or statutory that the capital instrument will be bought back, redeemed, or canceled. Tier 2 capital is drastically simplified and Tier 3 capital abolished. All capital instruments that no longer are eligible for Tier 1 or Tier 2 capital will be phased out over ten years, e.g. minority shareholdings, goodwill and intangible assets. Capital requirement is still 8%, but the capital composition has tightened up considerably. The quantity of the common equity especially needs to be increased, more precisely, from 2% (Basel II) to 4.5% by January 1, 2015. This leads to an increase of Tier 1 capital from 4% currently to 6% in the same period. The difference between the total capital requirement of 8% and the Tier 1 capital ratio can be met with Tier 2 capital.

In addition, the regulated institutions must gradually build up a capital conversation buffer which consists solely of common equity by 2019. This capital conversation buffer of 2.5% of the risk-weighted assets brings the total common equity ratio to 7% from 2019 onwards. Financial institutions are allowed to draw down the buffer to absorb losses during periods of stress. The closer their regulatory capital ratios approach the minimum requirements, the greater the cutback of earnings distributions. Additional capital buffers above the minimum requirement also contribute to a further increase in the capital base and can be drawn upon in periods of financial and economic stress. Whereas Basel II did not address capital buffers, Basel III introduces two different types which have to be met with common equity. The second buffer is the countercyclical buffer, within a range of 0- 2.5%, which will be implemented according to national circumstances and will regulate credit growth. Macroeconomic indicators, such as the gross domestic product (GDP), can be used to decide on the size of the buffer. This buffer is designed to avoid systemic risk. The macro prudential goal is achieved by dampening excessive, aggregated credit growth in the banking sector which can exacerbate crises. For instance, the collapse of the US sub-prime sector was triggered by excessive growth in the credit sector. A country will only put the buffer in effect when excess credit growth could result in a system-wide build-up of risk. In this case, the countercyclical buffer will be introduced as an extension of the capital conversation buffer. Financial institutions that have a ratio less than 2.5% will face restrictions on payouts of dividends, share buybacks and bonuses. Both buffers will be phased in beginning on January 1, 2016 and fully effective in January 2019. In the European Union, a further tool to prevent and mitigate macroprudential and systemic risks has been built into the CRD IV package[11]. Banks that have been determined to by systemically relevant are obliged to built up a systemic risk buffer as from

[11] See European Union (2013b).

2016, as well. As of 2019 this buffer should be fully built up. The amount of additional capital varies between 1-3% of the risk weighted assets, depending on the degree of systemic relevance. Higher levels of capital to absorb losses are essential to broader financial stability. A study of the Basel Committee suggests that an increase in the banking sector's common equity from 7% to 8% reduces the annual probability of a financial crisis by at least 1 percentage point[12]. This, in turn, produces an expected annual economic output benefit of between 0.2% and 0.6%. The financial institutions should achieve the new standards through earnings retention, de-risking of certain capital market exposures and appropriate capital raising, not through decreasing lending to the economy which would have a negative impact on the economic recovery after the recent financial crisis.

Next, the Committee has proposed to include two liquidity ratios in the regulatory framework to ensure that banks, which are internationally active, are able to withstand severe liquidity stress in the future. Liquidity risk was often disregarded and not considered to be a key risk at system level. Thus, in 2010 the BCBS adopted a document named Basel III: International Framework for Liquidity Risk Measurement, Standards and Monitoring[13]. Since then, globally uniform minimum standards are introduced. This has been the least harmonized area of banking supervision. The aim is to ensure that internationally active banks are able to withstand severe liquidity stress in the future. The short term LCR insures that sufficient liquid assets are available to meet any cash flow gaps throughout a 30 day system-wide liquidity shock and be no lower than 100%. Generally, the higher the value of the ratio, the larger the margin of safety that the financial institution possesses. Accordingly, the more robust is their structural liquidity profile. The same applies for the NSFR. This ratio complements the short-term minimum standard and promotes resilience

[12]See Basel Committee (2010c).
[13]See Basel Committee (2010b).

over medium and long-term time horizons. The NSFR aims to ensure funding of investment banking inventories, off-balance sheet exposures, securitization pipelines and other assets and activities of banking organizations with at least a minimum amount of stable liabilities in relation to their liquidity risk profiles. The financial institutions have less experience with those ratios but have to self ensure against acute liquidity stress scenarios. Therefore, the Basel Committee decided to phase them in gradually, i.e. before introducing the minimum standard, an observation period of four years is planned.

Furthermore, the capital requirements for counterparty credit risk are also strengthened. Extensive changes to the capital charges for counterparty risk are included in the package of Basel III. These exposures, particularly arising from derivatives, repos and securities financing activities, are required to be measured using stressed inputs. During the financial crisis, heavy losses on derivatives transactions were induced by increased credit value adjustments. Financial institutions have to hold capital for mark-to-market losses associated with the deterioration of counterparty's credit quality. Higher capital requirements imply incentives to transfer over-the-counter (OTC) activities to a central counterparty. The creation of a new concentration of systemic risk needs to be avoided by managing and capitalizing them appropriately.

After presenting the risk-based capital requirements, the explanation of the non-risk based "backstop" follows. As stated above, the focus of the analysis is on the non-risk weighted LR. It is widely believed that excess leverage by banks contributed to the global banking crisis. To address this issue, a risk independent LR is introduced as an additional prudential tool to complement the capital requirements. As discussed in Luoma and Spiller Jr (2002), leverage allows a bank to increase potential losses or gains on an investment or position, beyond the possibility of its own funds. Balance sheet leverage is widely recognized and the most visible form of leverage. A balance sheet is leveraged when a bank's assets exceed its equity base. Banks generally acquire more assets to increase their return on equity. Invisible leverage exists, also, for instance, off-balance sheet leverage, which is based on market-dependent future cash flows, is considered as economic leverage. A widely used measure of leverage is the LR that addresses both balance sheet and economic leverage. The regulatory purpose is to limit the level of a bank's debt. Banks will not be able to reduce their leverage by selling assets in periods of stress, which puts market prices under pressure and leads to a declining value of assets that banks continue to hold on their balance sheet. The BCBS will test a minimum LR of 3%[14]. This ratio will be phased in cautiously and binding for every financial institution. The focus is put on this new regulatory measure in Section 3.1.1 where an in-depth discussion follows.

To sum up, the Basel III framework will both, amend risk weighted capital requirements and superimpose a non-risk weighted LR. Including risk weighted measures obliges banks to assign capital depending on how risky their assets are. The criticism that was voiced in the aftermath of the financial crisis, was that the Basel II rules encouraged financial institutions to purchase mortgage-backed securities by assigning these securities a low risk weight. Ironically, the Basel III framework will provide an even stronger incentive for banks to purchase sovereign debt instruments issued by countries in Europe that are facing significant economic problems. To see this, the Basel II rules[15] for risk weighting banking book exposure are recalled. Generally risk weights for sovereign debt were determined depending on the rating for each country. Thus, claims on sovereigns and their central banks were risk weighted under the Basel II framework as presented in Table 2.2. As stated in the Basel II framework, solely

[14]See Basel Committee (2010a) for further details on the recommendations of the BCBS.
[15]See Basel Committee (2006) for the complete framework.

Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to BB-	Below B-	Unrated
Risk Weight	0%	20%	50%	100%	150%	100%

Table 2.2: Basel II: risk weights of sovereigns and their central banks

claims on the Bank for International Settlements, the International Monetary Fund, the European Central Bank and the European Community received a 0% risk weight. The system of risk weighting under the Basel III framework, however, ascribes zero weight to certain sovereign debt. As stated by the European Union in its Capital Requirements Regulation the risk weight assignment to exposures to the European Central Bank is unchanged and remains to be a 0% risk weight[16]. As opposed to Basel II, exposures to Member State's central governments, and central banks denominated and funded in the domestic currency of that central government and central bank is assigned a 0% risk weight, also. Basel III rules oblige banks to assign capital depending on the risk of the sovereign assets, but Euro-zone banks have a workaround. Thus, lenders are getting away with holding no capital against their eurozone sovereign debt. Moreover, Basel III assigns the risk weight of 0% to sovereign debt of many countries experiencing economic stress such as Ireland, Greece, Portugal, Italy and Spain. Debt issued by these countries is coupled with higher returns due to paying significantly higher interest rates than, for example, comparable US Treasury instruments. However, no higher capital charge is required under the Basel III proposal. The low capital charge and the expected higher returns provide a strong incentive for some financial institutions to increase their exposure to risky foreign country debt. This incentive has the politically pleasing effect of keeping sovereign borrowing costs low. Bank investors are worried that lenders are not holding enough capital. This provides additional evidence that the proposal of Basel III needs to align a non-risk weighted measure. The LR is

[16]See European Union (2013b), Article 114.

introduced as a supplementary measure to the risk-based capital requirements. A non-risk weighted measure can reduce both, the incentive to understate risk and the incentive to stock up on high risk government bonds in order to avoid higher capital requirements. However, it is up for discussion what will occur when this non-risk based regulatory measure is introduced. Banks may try to game this measure just as they game the risk weighted capital requirements. Accordingly, the LR proposal may have the unintended consequence of actually increasing the risk in the financial system rather than reducing it. The thesis provides further evidence on this subject.

After establishing a common understanding of the term Basel III, the broadly discussed term 'financial stability' is to be defined. International banking regulation and supervision reflects the growing prominence of financial stability objectives. Financial stability, which is not directly observable, has become a core component of regulation reforms. Among others, Crockett (2000) argues for distinguishing between two dimensions of financial stability: the micro- and macroprudential dimensions. The former is characterized by the soundness of individual institutions in the financial system. The objective is to limit "idiosyncratic risk", i.e. limiting the likelihood of failure of each institution and thus protecting depositors. The latter is characterized by the stability of the financial system as a whole. Its objective is to limit "systemic risk", i.e. limiting costs to the economy from moral hazard induced by regulation or financial distress. The likelihood of failure, not of individual institutions, but of significant portions of the entire system is to be limited. The focus of the macroprudential perspective is on the risk of correlated failures and pays attention to institution specific characteristics which are significant for the economy, such as size, while the microprudential dimension is not concerned with correlations and considers individual institutions in its own right. It might be expected that the health of the financial system is represented by the soundness of its financial institutions. Morris and Shin (2008) argue that to enhance financial stability at the macro-level, soundness at the individual level needs to be achieved simultaneously. This achievement is quite difficult because actions to ensure one institution's soundness are specific to this institution and may not be consistent with enhancing the soundness of another institution. In addition, objectives of financial stability may differ in the macro- and microprudential dimensions. For instance, cutting back on lending in a recession is only natural for individual banks, but if all banks tighten their lending standards, a further deterioration in the credit quality of portfolio at system level can be expected. By all means, enhancing the soundness of a particular institution should not stand in conflict with maintaining the stability of the whole financial system. Further, it is agreed that vulnerable or even insolvent banks may weaken the entire system due to systemic risk. Thus, promoting each individual's soundness is an encouraging start to achieving overall financial stability. Banking supervisors tend to have a greater microprudential focus. For instance, minimum capital requirements did not differentiate between banks according to their size and/or significance for the economy under Basel II . Also, the Basel II accord shall be deemed to have too much of an institution-specific focus and have lost sight of macro prudential elements. Supervisors try to consolidate a shift in perspective, complementing the microprudential dimension with increased awareness of the macroprudential one. There is agreement among the central bank governors of the G10 countries that the Basel III framework is a fundamental strengthening of global capital standards. The accord fixes many of the shortcomings of micro-level supervision and also incorporates the broader system wide focus by introducing macro prudential measures. In addition, the European Union incorporates into the revision of the CRD IV package a number of tools to prevent and mitigate macroprudential and systemic risks. Nevertheless, the opinions on the new Basel III accord are likely to diverge strongly. Still, there are many points open for discussion and the BCBS faces major challenges in handling financial instability at system level. For instance, the current European sovereign debt crisis, which principally emerged from Greece in May 2010, triggers a serious concern that the financial stability of the Euro area is put at risk at sovereign and individual bank level. This crisis contributes to underlying severe tensions in euro-area sovereign debt markets and, overall, to European financial instability.

In order to make a precise and explicit statement about a bank's individual solvency, a measure has to be defined to value the overriding understanding of the term 'financial stability'. It is useful to create an indicator which is able to disclose changes in the distress of banks over time. In this context, financial stability is defined in terms of the Distance to Default (DD) and the Probability of Default (PD) of individual financial institutions in this thesis. An in-depth discussion of these measures follows in Section 3.1.2.

2.3 Literature Review

There are two literatures which are directly related to this thesis. First of all, the literature which is central to bank regulation is reviewed.

Regarding the first aspect of this research, financial regulation, there is an abundant literature on Basel II. Amongst others, Adams et al. (2004), Repullo and Suarez (2004), and Liebig et al. (2007) examine the Basel II framework. Due to the up-to-dateness of the new regulatory framework, Basel III, just a few studies have been published. A brief review of academic literature on Basel III is given in the next paragraph. The new requirements are mostly supported. Morris and Shin (2008) is in line with the view of the Basel Committee (2009). The authors argue that excessive leverage leaves the financial system vulnerable to a sudden reversal, and thus a LR is necessary as a binding constraint. Hellwig (2010) supports the idea of introducing a LR requirement as well. He argues for ratios well beyond 10% in order to provide a robust buffer against high losses. He even goes a step further by proposing to replace risk-sensitive capital requirements. In his opinion, this will be the only possibility to limit gaming the risk-based measures. Blum (2008) analyzes capital requirements under Basel II and supports the idea that a risk-dependent measure is needed to induce "truth telling" in risk reporting. In addition, the author describes the LR as a ceiling on the put option value of limited liability. The leverage constraint forces banks to invest more of their "own" money and thus bear a larger part of the downside risk themselves. He rationalized the LR by presenting a theoretical model that examines the pros and cons. Blum (2008) concludes that a LR should have already been in place under Basel II, even though, he asserts that, as a consequence, low risk banks are disadvantaged. These banks have to hold more capital than would be socially optimal or efficient.[17] In contrast, "risky" banks may hold too little capital relative to the risks.

However, the key elements of Basel III have not always gained acceptance. Critical voices have emerged in literature and illustrate that, at least, some elements are roundly rejected by academic researchers. Kashyap et al. (2010) examine the impact of higher capital requirements, the focus being on large financial institutions. They conclude that, firstly, the new capital requirements need to be phased in gradually because costs of raising "fresh" equity are higher than the ongoing costs associated with holding equity. Secondly, an impact on the cost of loans is conceivable, but it is only a modest impact and not a major concern for customers. Finally, even though the effects on loan rates are expected to be modest, concerns about decreasing credit activity and a migra-

[17] Blum (2008) makes the assumption that capital is socially costly and defines a social waste by high opportunity cost of capital, i.e. banks that have more capital than necessary to avoid insolvency. This is a quite standard assumption in banking literature.

tion of this activity to the shadow-banking sector are raised. This potentially leads to an increase in fragility of the banking system as a whole. Kiema and Jokivuolle (2011) provide theoretical evidence that a LR requirement in combination with the risk-based capital requirements might affect loan pricing and quantities. The authors conclude that loan volumes remain unchanged. Further, they show that, in order to obtain high LRs, low-risk lending rates might increase and high-risk rates decrease which leads to an eventual risk-shifting from low-risk loans to high-risk loans. According to the authors, the only opportunity for low-risk loan banks to cope with LR requirement is to include high risk loans in their portfolios. In this context, this restriction might reduce bank soundness, counter to regulatory intentions. Hakura and Cosimano (2011) study the same effect using an empirical model. The authors analyze the higher capital requirements under Basel III on bank lending rates and loan growth using data of the 100 largest banks worldwide over the period from 2001 to 2009. As empirical strategy, a generalized method of moments estimation procedure is used. Two regressions are run: the first one to analyze the optimal level of capital and the second one to investigate the bank's loan rate. It is concluded that with an increase in required capital, the marginal cost of loans (defined as the weighted average for the marginal cost of equity and deposits) will increase, as long as the cost of equity exceeds the cost of deposits. This increase in loan rates, in turn, declines loan growth in the long run. Frenkel and Rudolf (2010) examine the macroeconomic and financial effects of a LR requirement. Similar to the findings of Hakura and Cosimano (2011), the study concludes that this constraint on banks' business activity creates undesirable incentives, such as, cutting back on lending, which could lead to a slowdown in economic activity. Overall, the authors endorse higher levels of equity but conclude that a LR requirement increases vulnerability rather than bank soundness. Miu et al.

(2010) study the new capital stability rules by Basel III from a theoretical and empirical standpoint, putting the focus on capital buffers rather than on the LR. However, the authors conclude that introducing a LR seems to be redundant and not connected to current practices in risk optimization. In addition, financial institutions should not rely on these capital buffers but rather improve the capital quality. Kamada and Nasu (2010) provide theoretical and empirical evidence that a constraint on leverage requirement has side-effects by impacting the quality of assets. Asian banks and banks in the G10 countries are compared by using an asset quality index as the key concept. Not distinguishing different types of bank assets by their riskiness could be disadvantageous by increasing the effective capital requirement on low-risk assets. The authors conclude that one possible reaction to the LR is that banks will shift their asset portfolio from safer to riskier assets. Therefore, ignoring any potential differences in risk profiles may arise another inherent limitation. In addition, it is argued that local conditions of business models and financial environment should be considered when adopting a LR.

To sum up, recent literature on Basel III, more precisely, on the new non-risk-weighted LR, is not in agreement and there is need for further research. On the one hand, the new framework gains increasing acceptance by academic researchers, but on the other hand, possible side-effects of the LR, counter to regulatory intentions, are being discussed. Two of these side-effects could be increasing loan rates and decreasing loan volumes.

The second related literature studies how to best estimate financial stability and predict corporate default risk. It is a widely discussed topic in credit risk research. Economic theory provides different approaches to measure firm's default probability. In particular, recent empirical and theoretical studies discuss different indicators of corporate bankruptcy prediction[18]. The option pricing model developed by Black and Scholes (1973) and Merton (1974) has prevailed. The model to forecast defaults is a market data based one. Instead of using the book value of debt, the main input to estimate the indicator Distance to Default (DD) is the value of equity and its volatility. Duffie et al. (2007) show the model's predictive power of default probabilities over time for US industrial firms. In industry practice the Merton model was first adopted by Moody's KMV[19]. These practitioners are a leading provider of company default risk analysis and focus on the determination of default probability for all publicly traded firms. In contrast, financial institutions are usually very opaque. Chan-Lau and Sy (2007) argue that the structure of liabilities is very different compared to non-financial institutions and banks are often tightly regulated. Thus, calibrating the model on banks introduces some challenges. However, Crosbie and Bohn (2003) confirm the applicability of this model on financial institutions and its overall excellent performance in detecting bank vulnerability. Regulatory actions, or rather signals when regulators should intervene or banks should take corrective actions themselves, are ignored. Even though this method has been initially adopted to company default risk, empirical research exists showing that the concept of the DD is a predictive power to detect individual bank distress. In this context, Gropp et al. (2004) compare the performance of commonly applied bankruptcy prediction models. The DD and bond spreads are applied as indicators to signal bank fragility using market and balance sheet data of European banks over the period from 1991-2001. Empirical results show that both indicators are suitable to predict bank soundness. Particularly the DD is a suitable and all-encompassing indicator of financial stability because this method covers all essential bank risk elements such as the value of asset, as-

[18]See, amongst others, Miller (2009) and Bharath and Shumway (2008).
[19]See Crosbie and Bohn (2003).

set volatility and leverage. However, predictive power of the DD is poor when failure of a bank is close. Still, the authors support the idea that the DD indicator may even outperform other indicators such as bond spreads. Gropp et al. (2006) summarize and extend the results obtained by Gropp et al. (2004). Harada and Ito (2011) detect empirical evidence of the usefulness of the DD to measure pre- and post-merger performance of large Japanese banks in the late 1990s and 2000s. The findings show that a merger is not a guarantee for an improvement in bank soundness and does not help banks to escape from failure. Financial health of the merged bank depends on the soundness of the pre-merged banks. In addition, merged banks often produce a negative DD right after the merger. Thus, the financial system in Japan did not benefit from the mergers in terms of financial soundness. Harada et al. (2010) provide further evidence for the predictive power of the DD. Eight Japanese banks were examined by calculating and analyzing the DD and a DD spread[20]. Generally both indicators were reliable in forecasting the default of those banks. Based on a contingent claims analysis, Saldías (2012) develops an aggregated DD series to monitor vulnerabilities in the European banking sector using a dataset of the largest, systemically important banks in Europe between 2002 and 2012. Two indicators are generated: an average distance to default using individual equity options and a portfolio distance to default using STOXX Europe 600 banks information. If both indicators and their gap are employed to monitor systemic risk, the analysis is notably enhanced. Due to the forward-looking feature of the DD, this approach allows an early signaling of distress. Vulpes and Brasili (2006) apply a dynamic factor model to measure co-movements in EU-15 bank's risk during the period from 1994 to 2004. This model allows one to decompose the DD into three components: a country-specific, an EU-wide and a bank-level idiosyncratic component. The authors rely on Gropp et al. (2004) and confirm

[20]The DD spread is defined as a DD of a failed bank minus the DD of sound banks.

the suitability of this indicator to signal bank fragility. Michalak (2011) utilizes the concept of the DD to provide empirical evidence that an increase in short term interest rates has a negative impact on a bank's soundness. The author uses data from stock-listed Western European banks over a period from 1997 to 2008. The DD, more precisely, the Expected Default Frequency is used as a proxy for the vulnerability of those banks. The related theoretical and empirical work mentioned above reveal that the concept of the DD has become a popular proxy for bank soundness. This indicator is used for research concerning financial stability, systemic risk, and banking crisis.

To conclude, a rich literature on the role of the DD in credit risk research has emanated. Not only practitioners, but also researchers consider the DD as a reliable indicator for financial stability. Based on the theoretical and empirical evidence on the predictive power of the DD to measure banks' default risk, this indicator is used for further research in this thesis. Furthermore, recent contributions of literature cover bank regulatory issues. Yet, opinions differ whether the regulatory framework by the BCBS increases financial stability or rather vulnerability. Overall, theoretical and empirical literature is not conclusive about the relationship between the Basel III framework and financial stability. Empirical studies on this topic are rather scarce. In particular, the linkage between the key concept of the DD, as an indicator for financial stability, and the non-risk weighted regulatory measure has not been covered in recent literature.

Chapter 3

Financial Risk Analysis

This chapter reports on financial risk in the global banking sector. With a view to the investigation of the nexus between the LR and financial stability in Chapter 4, this thesis will now look at the regulatory and stability measures are examined independently from both theoretical and empirical perspectives. Analyzing the LR of individual banks gives information on the capitalization of the banking sector. Compared to the calibration target proposed by the BCBS, it can be examined if banks are adequately capitalized, and thus considered to be healthy and sound. Furthermore, default risk has been modeled by the distance to default (DD) and the probability of default (PD) to monitor the soundness of financial institutions in recent years. These are popular indicators due to encompassing most elements of bank risk. The financial soundness measures are calibrated in order to investigate individual bank distress and overall banking system fragility.

The chapter is organized as follows. In Section 3.1, theoretical underpinnings are discussed. Section 3.2 presents the bank sample used for empirical research done in this and the following chapter. Furthermore, this section describes the application of the measures to the data set. Section 3.3 reports empirical results for the LR series, the DD and PD series, respectively. Finally, Section 3.4 concludes.

3.1 Theoretical Underpinnings

This section presents the theoretical background and technical discussion of the relevant measures for this work. First, the LR as proposed under the Basel III framework by the BCBS is discussed. Then, the DD and PD are considered by applying the Black-Scholes-Merton model as theoretical framework.

3.1.1 Leverage Ratio Requirement

The LR requirement as proposed by the BCBS, is presented and discussed in the following consultation papers: Basel Committee (2009) and Basel Committee (2010a). Not only does the BCBS believe, but it is widely believed that the build-up of excessive on- and off-balance sheet leverage at individual bank level, as in the financial system, contributed to the global banking crisis. Furthermore, the Basel III framework gives financial institutions the incentive to understate risk in order to avoid the higher capital requirements. Finally, banks can have an incentive to stock up on exposures to risky sovereign debt, see Section 2.2 for further details. To address these issues, the Basel Committee supplements the Basel II risk-based framework with a non-risk based level of capitalization, i.e. risky assets attract the same regulatory requirement as safe assets. The control parameter serves as a backstop to the other risk-sensitive measures. It has been discovered that the high levels of leverage which were monitored prior to the crisis, were not accurately accounted for in the risk-based capital requirements of the Basel II framework. The decision to introduce a LR was endorsed by the Group of Central Bank Governors and Heads of Supervision, the Committee's governing body on September 7th, 2009, and supported by the G20 leaders at the Pittsburgh Summit in September 2009. The objectives were the following:

- containing the build up of excessive leverage in the banking sector,
- introducing additional safeguards against model risk attempts to game the risk based requirements.

Acharya (2009) argues that many on- and off-balance sheet items that turned out to have substantial risk in the global financial crisis, indeed received very low risk-weights under Basel II. Prior to the crisis, banks had shown strong risk based capital ratio while building up excessive leverage. When the financial crisis occurred, banks with excessive leverage were forced to deleverage. The downward pressure on asset prices increased which encouraged banks to further deleveraging. These banks entered a downward spiral in asset values, and experienced increased losses and reduced capital levels. By putting a limit on the level of a bank's debt, the risk of the destabilizing deleveraging processes, that can damage the economy and the broader financial system, can be mitigated. Precisely, the deleveraging dynamic in periods of stress are reduced because the build-up of excess leverage in good times and maturity mismatches will be constrained. Thus, the LR is considered as a binding constraint on the upside of the cycle which is characterized by ample funding conditions. Morris and Shin (2008) argue that banks are able to increase their leverage easily in a boom dynamic but are often forced to deleverage in periods of financial stress. In recent literature not only the desirable uses of the proposed LR from the perspective of maintaining financial stability are discussed, but also a number of side effects that may arise when introducing the LR as a supplementary measure to the risk-based capital requirement. Some academic researchers such as Kiema and Jokivuolle (2011) or Frenkel and Rudolf (2010) argue that negative financial and macroeconomic effects outweigh the benefits of introducing a LR constraint.

More precisely, widely discussed is the negative impact on asset quality, loan rates and volumes at individual bank level and thus the increasing fragility in the banking sector[1].

The LR will be phased in cautiously, i.e. supervisory monitoring the first two years and testing during a parallel run starting in 2013. Based on the results of the parallel run period and appropriate review and calibration, final adjustments will be made with a view to migrating to Pillar 1 treatment in 2018. The LR, as proposed by the BCBS, and finally, adopted by the European Union, can be written as follows

$$LR_{BCBS} = \frac{Capital}{Total\,Exposure}\,, \tag{3.1}$$

where $Capital$ and $Total\,Exposure$ require a definition. For the capital measure the Committee intends to consider common Tier 1 capital and the additional going concern Tier 1 capital as possible measures. Thus, total Tier 1 capital, as defined by the Basel III framework, can be considered. Common equity basically consists of common shares, stock surplus and retained earnings. All elements of Tier 1 capital are listed in paragraphs 52 to 56 of Basel Committee (2010a). The generally preferred total exposure, or assets measure, follows the accounting measure. Advantages of this approach is that accounting data is available and generally not risk-based. The Committee also discussed whether or not to include off-balance sheet items in the measure of exposure. First of all, there is a common understanding that these items were a significant source of leverage during the last crisis. Secondly, excluding them could create an incentive to shift items off the balance sheet to avoid the LR constraint. The European Union decided to incorporate off-balance sheet items into the total exposure measure[2]. To begin with, 3% is the calibration target for the Tier 1

[1]See, amongst others, Kamada and Nasu (2010) or Hakura and Cosimano (2011). Further details are given in the literature review, see Section 2.3.

[2]See European Union (2013b).

capital to total exposure ratio which should be reported as the average of the monthly LR over the quarter. The ratio applies on a consolidated basis, as well as, at the level of individual banks. The benefit is that introducing the LR is nearly costless due to its relative simplicity. Hence, the LR restriction will be binding for every financial institution. The idea is that a wide range of countries will adopt an internationally harmonized and appropriately calibrated ratio in the future. Competitive disadvantages due to the lack of standardized assumptions surrounding the calculation in each accounting regime can emerge and have to be taken in consideration. Moreover, LRs can vary across countries and lead to a lack of comparability among them. The BCBS states that the details of the ratio will be harmonized internationally to ensure comparability by adjusting for remaining differences in accounting.

As stated by Federal Deposit Insurance Corporation (2011), a restricted LR is already in place in the United States. This country imposed a LR requirement on regulated banks, laid down in Pillar 2 of the Basel II framework. The ratio is expressed as Tier 1 capital to total average adjusted assets, defined as the quarterly average total assets minus intangible assets, such as goodwill, software expenses, and deferred taxes. Off-balance sheet items are not included in the exposure measure. The ratio is set at 3% for banks rated "strong" and at 4% for all other banks. In addition, banks are subject to prompt corrective action rules, requiring them to maintain a LR of at least 5% in order to be considered well capitalized. Table 3.1 presents the capitalization categories which can be found in the rules and regulations of the Federal Deposit Insurance Corporation (2011). Whether or not US banks managed their way through the crisis better than the European countries, remains to be seen. Switzerland is another country which introduced a LR under Pillar 2 of the Basel II framework in 2008 but solely for two banks: Credit Suisse and UBS. Their calculation is equal to the US LR. The

Capitalization category	LR
Well capitalized	$\geq 5\%$
Adequately capitalized	$\geq 4\%$
Undercapitalized	$\leq 4\%$
Significantly undercapitalized	$\leq 3\%$
Critically undercapitalized	$\leq 2\%$

Table 3.1: Capitalization category by Prompt Corrective Action Rules

minimum level is set to 3% at the consolidated level and at 4% at individual bank level. Impacts of the introduction of a minimum LR in Switzerland and the US will be analyzed in Section 3.3.1.

Before turning to the empirical analysis of the LR, the results of the Basel III monitoring exercise are presented. This study, set up by the BCBS, examines the impact of the rules contained in the regulatory document "Basel III: A global regulatory framework for more resilient banks and banking systems"[3] on selected financial institutions. The exercise is based on rigorous reporting processes to review the implications periodically. The data collection takes place semi-annually using data as of end-June and end-December of each year. The first report on the Basel III monitoring is for German institutions and provided by the German Central Bank[4] (GCB). The second report provided by the European Banking Authority[5] (EBA) gives information on the results of the Basel III monitoring exercise at European level. The last one is published by the BCBS[6] itself, and presents the results at world level. To create comparability with the results presented in the financial risk analysis, Section 3.3.1, the reports at European and world level based on data as of December 31, 2011 are described. The results for German banks are only available based on data as of June 30, 2012. Note that only findings regarding the LR are presented. All other findings of the Basel III Monitoring exercise are neglected. All reports

[3]See Basel Committee (2010a).
[4]See Deutsche Bundesbank (2012).
[5]See European Banking Authority (2012).
[6]See Basel Committee (2012).

calculate two alternative measures of the LR. The differences refer to the numerator of Equation (3.1). The first measure is defined as the Basel III LR and exactly matches the definition of Equation (3.1). The second, is the Basel II LR which includes Tier 1 capital eligible under the Basel II agreement. The main difference consists in improving the quality of regulatory Tier 1 capital by recognizing hybrid capital instruments only as components of Tier 1 capital to a limited extent. These instruments are subject to much stricter conditions under Basel III. The denominator includes off-balance sheet items in both cases. For the interpretation of the results, the terminology used to describe a bank's leverage is clarified. Generally, when a bank is referred to being more leveraged, this refers to a multiple of exposure to capital. Hence, banks with high level of leverage have low LRs.

The EBA includes in its sample a total of 156 banks from 18 countries in Europe and further distinguishes between 44 banks of Group 1 and 112 banks of Group 2. Of interest is Group 1, because these banks have Tier 1 capital in excess of EUR 3 billion and are internationally active. All other banks are defined as Group 2. The exercise is carried out assuming full implementation of Basel III. It is reported that Group 1 banks show an average LR of 2.9%, while Group 2 banks' LR is slightly higher and stands at 3.3%. Therefore, 51% of the 41 participating Group 1 banks and 70% of the 111 Group 2 banks would meet the 3% benchmark as of the end of December 2011. In addition, the EBA provides findings regarding a hypothetical LR which is based on the current definition of Tier 1 capital eligible under the Basel II framework. Under this definition, the average current LR of Group 1 is at 4.1% and of Group 2 at 4.6%. Higher LRs under the Basel II Tier 1 definition result from the objective of improving the quality of the capital base under the new Basel Accord. Figure 3.1 reports the distribution of the results across participating banks for Group

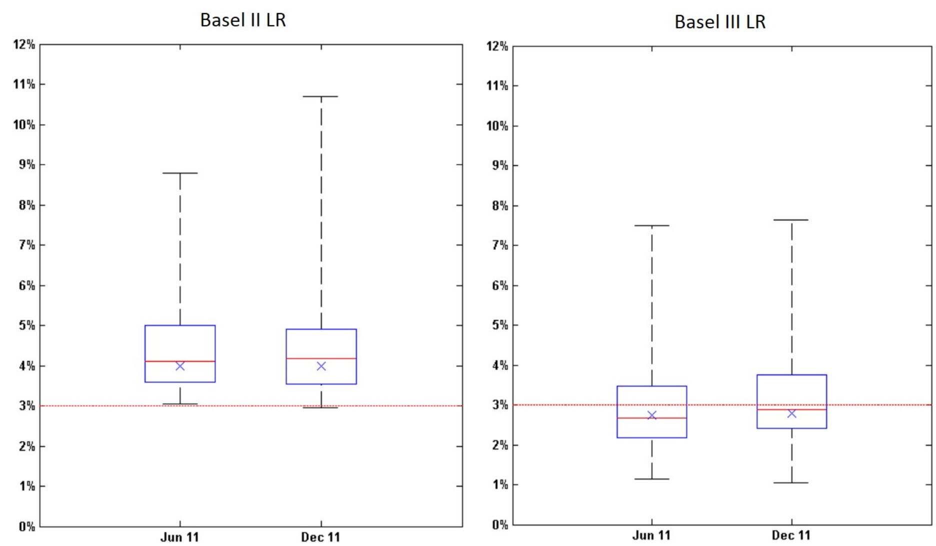

Figure 3.1: EBA - Basel II LR and Basel III LR of Group 1

This figure shows the distribution of the results of the Basel III monitoring exercise by the European Banking Authority. Source: European Banking Authority (2012), p. 20-21.

1 as of June 2011 and December 2011. On the left the LR using Tier 1 capital according to Basel II rules, and on the right the LR using the fully phased-in Basel III definition of Tier 1 capital is illustrated. The dashed red lines show the calibration benchmark of 3%, while the thin red lines represent the median. The mean is shown as "x". The blue box is defined by the 25^{th} and 75^{th} percentile value while the the 5^{th} and 95^{th} percentile are represented by the lower and upper end points of the black vertical lines. The EBA concludes that the average LR has improved slightly compared to the previous report.

The BCBS reports that a total of 209 banks from 26 countries world wide participated in their study. The same definition of Group 1 as stated above applies, including 102 banks, while Group 2 includes 107 banks. Data is collected as of 31 December 2011 at the consolidated level. Findings regarding the LR are as follows: the average Basel III LR for the entire sample is 3.6%, while the average for Group 1 is at 3.5% and for Group 2 at 4.4%. Overall 73% of the entire sample, 72% of Group 1 and 75% of Group 2, would meet the target of 3% as of December 2011. Using the Basel II Tier 1 capital definition, the mean for all banks is 4.5%, for Group 1 is 4.4% and for Group 2 is at 4.9%. 93% of all banks, 96% of Group 1 and 91% of Group 2, would meet the target.

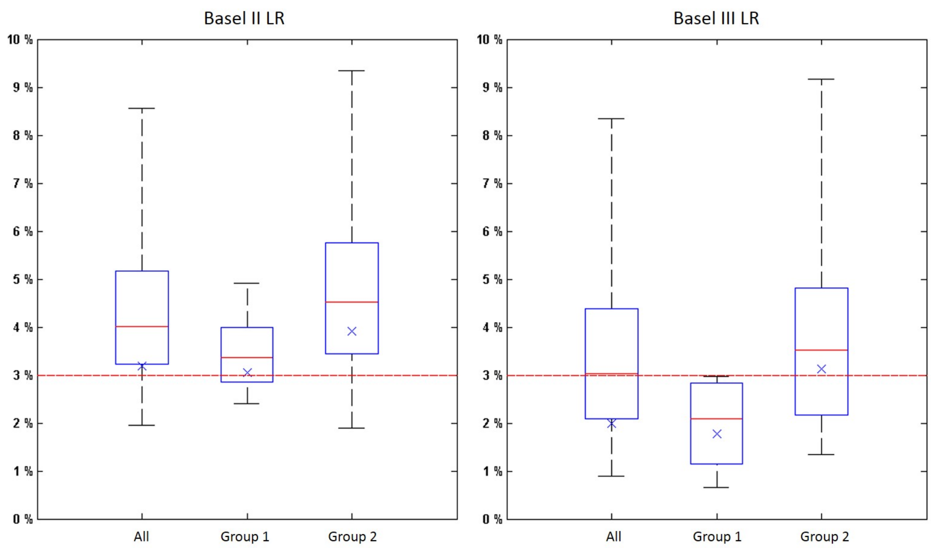

Figure 3.2: GCB - Basel II LR and Basel III LR (all, Group 1, and Group 2)

This figure shows the distribution of the results of the Basel III monitoring exercise by the German Central Bank. Source: Deutsche Bundesbank (2012), p. 21.

The German Central Bank reports results as of 30 June 2012 and includes a total of 33 German banks in their sample of which 8 banks are considered Group 1 and 25 Group 2 banks. The average Basel III LR for all banks is at 2.0%, for Group 1 banks at 1.8% and for Group 2 banks at 3.1%. 52% of the entire sample would meet the calibration target of 3%. Further information on individual groups is not given but visible in Figure 3.2. The figure illustrates the Basel II LR and Basel III LR for the entire sample, Group 1 and Group 2, using a box plots diagram as well. Using the Basel II definition of Tier 1 capital, the average LR for all 33 banks is 3.2%, Group 1 at 3.0% and Group 2 at 3.9%.

Overall, the monitoring indicates a positive correlation between the level of leverage and bank size since the mean of the LR for Group 1 banks is significantly lower than for Group 2 banks. It can be concluded that Group 2 banks are less leveraged on average. This difference increases under Basel III. Nevertheless, the changes in the definition of capital under Basel III is likely to affect Group 1 banks to a greater extent than banks in Group 2. Results are recapitulated in Table 3.2. Regarding Group 1, it can be concluded that German banks on average have the lowest LRs. Values improve at European level, and including banks at world level increases the weighted average LR again. Findings regarding the LR for Group 1 provided by the EBA and the German Central Bank are subsequently compared to the empirical results in the Section 3.3.1.

	Basel II LR (%)		Basel III LR (%)	
	Group 1	Group 2	Group 1	Group 2
EBA*	4.1	4.6	2.9	3.3
BCBS*	4.4	4.9	3.5	4.4
GCB**	3.0	3.9	1.8	3.1

Table 3.2: Results Basel III-Monitoring
*as of 31 December 2011
**as of 30 June 2012

3.1.2 Financial Soundness Measures

Next, the theoretical background and the technical discussion of the DD and PD are presented by applying the Black-Scholes-Merton framework.

Theoretical Background

Crosbie and Bohn (2003) argue that the most effective measure of default probability derives from models that employ both financial statements and market prices. Thus, the authors explain that measuring default risk requires certain accessible types of information: market prices of the bank's debt and equity, financial statements and appraisals of the bank's prospects and risk. Market prices are inherently forward looking. They combine investor's willingness to sell and buy equity and debt securities of the bank, and therefore embody investor's views and forecasts. In the determination of default probability, prices can enhance considerably to the predictive power of the estimates. As a method to assess and evaluate a bank's soundness, the concept of the distance to default (DD) and probability of default (PD) is proposed. In general, the probability of default of a bank is determined by three main elements: (i) the market value of assets, (ii)asset value risk, and (iii) leverage. The former represents the present value of the free cash flows in the future, produced by the bank's assets, discounted at the appropriate discount rate. The pertinent measure is always the market value. The second element should always be linked to the uncertain estimate, the value of assets. The latter is a measure of the extent of the bank's contractual liabilities measured as the book value of liabilities. Initially, this method had been disseminated by the proprietors of the KMV corporation to monitor company default risk and has gained prominence since then. Financial soundness measures are calculated using a structural model based on the option pricing theory by Black and Scholes (1973) and Merton (1974). Crosbie and Bohn (2003) describe this particular application of the classic bond pricing model of Merton (1974) that was developed by Moody's KMV in detail. For simplicity, it is considered that a bank liability structure consists of equity and junior subordinated debt, i.e. each bank issues just one unit of equity and one zero-coupon bond. The sum of the values is equal to the value of the bank. Underlying the structural approach, it is assumed that the payoff to shareholders of a firm is modeled as a call option on its market asset value and can be written as

$$E = max(0; V_A - D)\,, \tag{3.2}$$

where E is the payoff to equity holders, and V_A the value of a bank's assets which is equal to its debt D and its equity. The strike price of the option is defined by the face value of its debt, named the default point. This implies that a company or a bank defaults, when the market price drops below the strike price. As long as the market value of assets is below the default point, the payoff to shareholders is zero. If it is higher, bank's assets are used to pay debt holders, and then the residual value is distributed to equity holders. Thus, equity holders are residual claimants on the bank since they get paid after bondholders. As banks' assets decrease and move closer to the default point, the market value of the call option also declines. The normalized distance between these two values is called the DD, representing the first measure of bank distress in the following financial risk analysis. In related literature, the DD is a popular and widely used measure of banks' fragility. Gropp et al. (2006) argue that the DD provides easily interpretable signals and yields useful information on increased fragility if the following criteria is fulfilled: the bank's value of assets declines, the asset volatility or leverage increases. Thus, it has become a benchmark indicator to monitor health in financial institutions. Further, Gropp et al. (2006), Gropp and Moerman (2004) and International Monetary Fund (2009) demonstrate that the DD is a capable model to predict a serious deterioration in banks' condition.[7] This forward-looking measure, as discussed by Crosbie and Bohn (2003), considers both liquidity and solvency risk. The DD is defined by

[7] The literature review provides further information, see Section 2.3.

the number of standard deviations of the market value of assets away from the default point. For instance, a bank with a DD of 1.0 indicates that the default, within a specified time, is a one-standard deviation event. It is presumed that the fluctuation of the mark-to-market value of assets follows the recent historical value, using the current value as a starting point. The model defines that a bank defaults when the face value of debt is below the market value of assets. Hence, the default barrier or point is where these two values are equal. The higher the DD, the greater the distance of a bank from the default point, the lower the risk. Thus, an increase in the DD implies greater bank stability or soundness. A DD of zero does not indicate a bank failure at that point of time. Rather, a bank needs to earn extra profit and roll over short-term debts, or assets will be exhausted and the bank is highly likely to fail. Having a negative DD or a DD of zero means that a bank is technically insolvent but can survive on the cash flow basis due to rollover assumptions. Banks will often adjust their liabilities as they near default. Nevertheless, a bank is extremely vulnerable the more a DD approaches zero. A bank run event could cause a sudden bank failure at this point of time due to the shortage of liquidity. If two banks in the sample have the same distance (in the sense of standard deviation) from its default point, the DD and the level of default risks are the same.

The Black and Scholes (1973) and Merton (1974) model determines the value of assets and its volatility from the value of equity and equity volatility. Merton (1974) model is the genesis for understanding the nexus between the market value of the bank's equity and the market value of its assets. The option pricing model by Black and Scholes (1973) can be seen as a special case of the Merton (1974) derivative pricing model. It provides a useful framework and illustrates the technical details on estimating DD values. Once the unobservable variables, the value and volatility of assets, are known, the probability that the market value of assets declines to the bank specific default barrier within a given time horizon, can be calculated. Subsequently, the PD can be derived from the DD. By definition, the DD and PD have a negative relationship: a higher DD is associated with a lower bank default probability.

Prior to the technical discussion of the DD and PD, some critical questions concerning the application of these measures on financial institutions is discussed next. Crosbie and Bohn (2003) address some of these critical issues that arise, especially, in practice. First of all, the authors explain that an efficient equity market is not assumed. The market does not reflect all the relevant information about a bank's value, but the price reflects a summary of investor's forecasts and individual's or committee's forecasts cannot do any better. Consequently, the market, as a source of information regarding the value of a bank, is suitable. Further, the importance of off-balance sheet items is discussed. Off-balance sheet activities are common for financial institutions. Boot and Thakor (1991) show that the amount of off-balance sheet liabilities can be quite significant. Crosbie and Bohn (2003) give numerical evidence that the utilized model is robust to the precise level of liabilities. The authors increase the value of the default point taking off-balance sheet commitments into account, all other variables are kept the same. The corresponding DD in their example increases slightly and the PD value does not change at all. Thus, the model deals very well with off-balance sheet liabilities. The authors then argue that information from the bond or credit derivatives market does not need to be included in the PD model. Models that relate credit spreads to default probabilities are so-called reduced-form models. These models suffer from the noise in debt market data and hence, they can be difficult to parametrize. For instance, Gropp et al. (2004, 2006) apply bond spreads as an indicator to signal bank fragility in their bankruptcy prediction models. They show that the response of these spreads to an increase in the probability of default is non-linear, i.e. spreads have little response far away from default and a strong reaction close to default. Particularly, the information content is diminished in the case of banks, which markets expect to bail out in the case of difficulties. In addition, more assumptions about the relationship between loss given default and default probabilities are required than in structural models. Crosbie and Bohn (2003) research concludes that structural models are more effective for estimations of default probabilities due to their empirical stability. This argumentation is in line with recent literature. Gropp et al. (2004, 2006) demonstrate that the DD outperforms or at least improves other financial stability measures such as bond or Credit Default Swap spreads. In contrast to Saldías (2012), Chan-Lau and Sy (2007) comment on possible shortcomings of the DD in banking. It is argued that supervisory and regulatory complexities associated with bank interventions and closures are not captured. The model assumes that a bank can use its total equity capital as a buffer. However, it is possible that supervisors or regulators intervene before its total capital is exhausted. Thus, the DD may not be suitable in order to analyze regulatory purposes. Crosbie and Bohn (2003) argue that interventions are costly to taxpayers most of the time, and that a default risk measure should not incorporate the uneconomic behavior of another group. Hence, a hard economic measure needs to be provided. In this financial risk analysis the DD is not used in order to predict bank failures, where government interventions can be of significance, but to assess and monitor financial soundness in the past. Hence, this limitation discussed by Chan-Lau and Sy (2007) is not alarming. Finally, it deserves notice that the financial soundness measures are estimated for the same industry but across different countries. Results are compared without taken the country of incorporation particularly into account. Due to differing accounting standards, one could argue that the results are biased. Crosbie and Bohn

(2003) show that the measure PD can be estimated appropriately for each bank regardless of its home country, and thus, is applicable across countries and even industries. The idiosyncrasies of different countries, in particular the economic prospects, are captured by the individual valuations of equity and assets. Hence, the authors conclude that the DD measure incorporates well, most relevant differences in default risk across countries. In the financial risk analysis the DD is preferred to analyzing a bank's soundness. The PD is derived from the DD in order to examine fundamental relationships in the panel data analysis in Chapter 4. Thus, both indicators are introduced. The variables that determine the DD and PD of a bank over a time horizon T are recapitulated and illustrated graphically from now until time T in Figure 3.3:

1. The current asset value $V_A(0)$.
2. The distribution of the asset value at time T.
3. The volatility of the future assets value at time T.
4. The level of the default point, the book value of liabilities.
5. The expected rate of growth in the value of assets over the horizon.
6. The length of the time horizon T

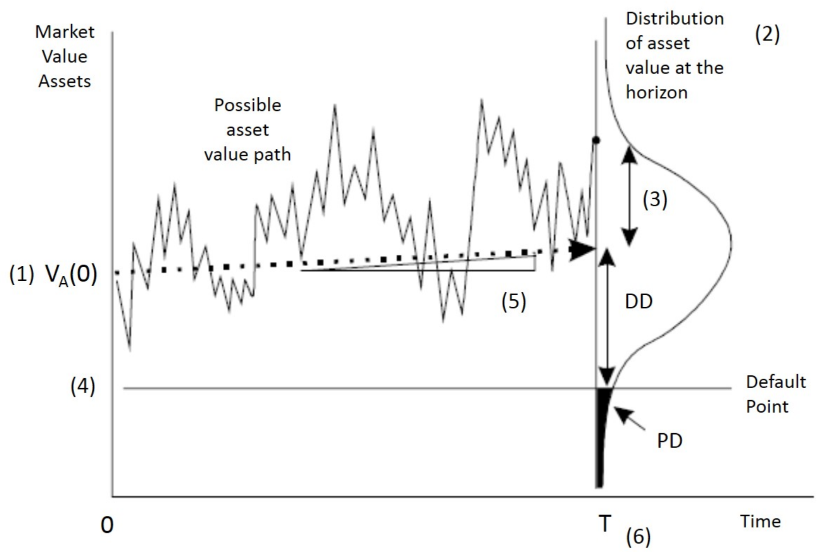

Figure 3.3: Determinants of the DD and PD

This figure shows the six variables that determine the probability of default of a bank over some horizon. Source: Crosbie and Bohn (2003), p. 13.

Technical Discussion

The numerical procedure to compute the financial soundness measures is presented next. The derivation of the DD is described in e.g. Michalak (2011) and Bharath and Shumway (2008). The PD is calculated using a two-step approach:

1. Calculation of the DD per bank i at time t,
2. Translation of the derived theoretical DD of bank i at time t into a time variant PD based on the risk neutral valuation framework.

The model recognizes that neither the market asset value nor its volatility is directly observable and exploits the option nature of equity to derive these values. Underlying the assumptions of the model, both unobservable variables can be inferred, amongst others, from the observable variables value of equity and equity volatility. In particular, the system of nonlinear equations for the option price and volatility is solved by an iterative procedure for the implied asset value and volatility. After inferring the value of assets and its volatility, the probability of default is specified in the model as a normal cumulative density function.

The Merton (1974) framework is employed to compute a bank's DD. Two important assumptions are made. First of all, the model assumes that under the empirical probability measure $\mathcal{P}$ the value of each bank follows a continuous-time stochastic process, in particular, a geometric Brownian motion,

$$dV_A = \mu V_A dt + \sigma_A V_A dW \,, \tag{3.3}$$

where V_A is the asset value of a bank, dV_A is the change in asset value, μ is the expected continuously compounded return on V_A, σ_A is the asset volatility and W is a standard Wiener process. The second assumption is that a bank has issued just one zero-coupon bond maturing in T periods. Under these assumption, the equity of a bank is a call option, as described above, with a time-to-maturity T. Applying the Black and Scholes (1973) formula, a bank's value of equity can be described as a function of its total asset value. The face value of a bank's debt is equal to the value of a risk-free discount bond minus the value of a put option on the bank. Again the strike price is equal to a bank's default point. The model stipulates that the bank's value of equity satisfies

$$V_E = V_A \cdot N(d_1) - D \cdot e^{-rT} \cdot N(d_2) \,, \tag{3.4}$$

where V_E is the market value of the bank's equity, D is the default point, r is the risk-free rate and $N(\cdot)$ is the cumulative standard normal distribution function,

d_1 is given by

$$d_1 = \frac{ln\left(\frac{V_A}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right) \cdot T}{\sigma_A \sqrt{T}}\,, \tag{3.5}$$

and d_2 is

$$d_2 = d_1 - \sigma_A \sqrt{T}\,. \tag{3.6}$$

Note that μ does not enter Equations (3.4), (3.5), and (3.6). By a standard argument an equivalent risk-neutral measure $\mathcal{Q}$ exists. Under $\mathcal{Q}$ all assets grow at the risk-free rate of interest r, i.e. all investors do not require any risk premium and can be treated as if they were risk neutral. Thus, $\mathcal{Q}$ is often called risk-neutral probability measure.[8] The price of the option, Equation (3.4), is given by the expected payoff of the claim under $\mathcal{Q}$.

Equation (3.4) expresses the value of equity of a bank. A second equation is used to determine the equity volatility by relating this volatility to the volatility of its assets. By Equations (3.3) and (3.4), and Itô's lemma we have

$$\frac{dV_E}{V_E} = \mu_E dt + \sigma_E dW\,, \tag{3.7}$$

where

$$\sigma_E = \left(\frac{V_A}{V_E}\right) \frac{\partial V_E}{\partial V_A}\, \sigma_A\,, \tag{3.8}$$

and μ_E is the expected return on equity under the probability measure $\mathcal{P}$. Black and Scholes (1973) and Merton (1974) show that $\frac{\partial V_E}{\partial V_A} = N(d_1)$, so that the asset volatility of a bank and its equity volatility are related by

$$\sigma_E = \left(\frac{V_A}{V_E}\right) N(d_1)\, \sigma_A\,, \tag{3.9}$$

[8]The probability measures $\mathcal{P}$ and $\mathcal{Q}$ are equivalent by Girsanov's theorem in continuous time models. See e.g. Musiela and Rutkowski (2005) for further details on this theorem and probability measures.

where d_1 is defined in Equation (3.5). Note that it is switched to the risk-neutral probability measure $\mathcal{Q}$.

To translate the value of equity and its volatility into a DD and a risk-neutral PD, these two nonlinear Equations, (3.4) and (3.9), are used. Thus, the model describes the unobserved option value as a function of different observable variables: the value of equity and its volatility, time-to-maturity, the face value of debt and the risk-free rate. While the unobservable value V_A needs to be inferred, V_E is easily observable in the market place by multiplying the bank's outstanding shares by its current stock price. Due to the nature of the model, the sample includes only stock listed banks. Similarly, equity volatility, σ_E, can be estimated from either historical stock returns or from option-implied volatility, while asset volatility, σ_A, must be inferred. Thus, the first step in implementing the DD model is to estimate the observable variables V_E and σ_E. In a second step, a forecasting horizon and a measure for the face value of a bank's debt needs to be defined. Due to unavailability of information about the maturity structure of liabilities, a common assumption is to use a time horizon of 1 year and take the book value of total liabilities to be the face value of the debt[9]. Thus, the default point in this model is given by

$$D = L_s + L_l\,, \tag{3.10}$$

where $L_s$is the bank's book value of short-term liabilities and L_l the book value of long-term liabilities. The next step is to generate values of the risk-free rate. After collecting this data, Equation (3.4) and (3.9) can be numerically solved for values of V_A and σ_A.

After obtaining the numerical solution, the DD can be calculated. Since per assumption the value of a bank's assets follows a log-normal distribution, the

[9]See e.g. Bharath and Shumway (2008) and Miller (2009).

log asset value in T years can be written as

$$lnV_A^T = lnV_A + \left(r - \frac{\sigma_A^2}{2}\right)T + \sigma_A\sqrt{T}\varepsilon\,, \tag{3.11}$$

where ε is the normally distributed random component of the bank's return on assets. The relationship given by that equation describes the evolution in the asset value path that is shown in Figure 3.3. The default point is given at $lnV_A^T = lnD$ and thus, the current distance d from the default point can be expressed as

$$\begin{aligned} d &= lnV_A^T - lnD = lnV_A + \left(r - \frac{\sigma_A^2}{2}\right)T + \sigma_A\sqrt{T}\varepsilon - lnD \\ \Leftrightarrow \quad \frac{d}{\sigma_A\sqrt{T}} &= \frac{ln\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2}\right)\cdot T}{\sigma_A\sqrt{T}} + \varepsilon. \end{aligned} \tag{3.12}$$

This yields the DD, which is defined as the number of standard deviations that a bank is away from the default point, D, within a given time horizon

$$DD = \frac{d}{\sigma_A\sqrt{T}} - \varepsilon = \frac{ln\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2}\right)\cdot T}{\sigma_A\sqrt{T}}. \tag{3.13}$$

Obviously, the DD increases with (a) an increase in bank asset value, (b) a decrease in asset volatility and/or (c) a decrease in bank leverage. Secondly, the DD of bank i at time t is translated into a time-variant PD. Sometimes the PD is called the expected default frequency[10]. Accordingly, the PD is defined as the probability that the market value of a bank's assets will be less than its book value of liabilities by the time debt matures and can be written as follows

$$P_T = Pr\left\{V_A^T \leq D_T \mid V_A(0) = V_A\right\}, \tag{3.14}$$

[10] See Michalak (2011).

where P_T is the probability of default by time T, V_A^T is the market value of the bank's assets at time T, and D is the book value of the bank's liabilities due at time T. The change in the value of the bank's assets is described by Equation (3.3) and thus, the value at time T, V_A^T, is described in Equation (3.11), given that the value at time 0 is V_A. Combining Equation (3.14) and (3.11), the PD can be written as

$$P_T = Pr\left\{lnV_A + \left(r - \frac{\sigma_A^2}{2}\right) \cdot T + \sigma_A\sqrt{T}\varepsilon \leq lnD\right\}. \tag{3.15}$$

After rearranging

$$P_T = Pr\left\{\varepsilon \leq \frac{ln\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2}\right) \cdot T}{\sigma_A\sqrt{T}}\right\}. \tag{3.16}$$

By symmetry of the normal distribution it follows

$$PD = N\left(-\frac{ln\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2}\right) \cdot T}{\sigma_A\sqrt{T}}\right) = N(-DD). \tag{3.17}$$

Equation (3.17) shows that the PD is a function of the distance between the value of a bank's assets today and the book value of its total liabilities adjusted for the continuously compounded expected return relative to asset volatility. Thus, a lower (higher) DD ratio implies a higher (lower) default probability.

3.2 Empirical Application

This section provides the dataset used to compute the LR, DD and PD series, and discusses particularities in the bank sample which are relevant for the following calibration. Further, the variables needed for the structural approach of calculation are defined and, finally, applied to the data. First of all, the calibration of the LR series is reported, then the calibration of the DD and PD series.

3.2.1 Dataset

The sample used to compute the LR and the financial soundness measures includes a total of 51 stock-listed banks from 16 countries headquartered in the Euro-zone, United Kingdom, Denmark, Sweden, Poland, Switzerland and the United States of America[11]. The sample period is determined from 2006 to 2011. The choice of the observation period permits one to monitor systemic risk over time during a crisis, years 2008 and 2009, and non-crisis period. In addition, not only effects of the global financial crisis are expected to play an important role, but also, the year 2011 could have been already affected by the European sovereign debt crisis. The sample consists of 47 banks located in Europe, accounting for more than a half of total assets in the EU banking system. Additionally four banks are included which are based in the United States. Amongst others, the largest banks ranked by total assets are given for each country. These banks are considered to be the core of the banking system in Europe and the US in terms of systemic risk, i.e. the largest systemically important financial institutions are included in the sample. There are some special cases worth pointing out.

The first one applies to the Concord Investmentbank AG in Germany. Data is only available for the years 2006 and 2007 due to bankruptcy. Insolvency filing was made in February 2009, and the bank was dissolved. The second and third cases are similar. The Dutch bank ABN Amro Holding N.V. and the English bank HBOS Plc were large and established banks, before these

[11] Denmark and United Kingdom are EU Member States with a special status. For the time being, they did not wish to adopt the euro. Sweden and Poland are EU Member States with a derogation. Both countries have not yet met the conditions for the adoption of the euro. For further details on this topic, see European Central Bank (2013).

banks were taken over by another large financial institution. The former was acquired by the Royal Bank of Scotland, Fortis and Banco Santander in equal measures in 2008. Data is available for year 2006 and 2007 in order to compute the DD and PD series. LR is calculated at individual bank level during the entire sample period. HBOS Plc was taken over by the English bank Lloyds TSB in 2008. Thus, this bank is a direct subsidiary of Lloyds TSB Bank Plc and a wholly owned indirect subsidiary of Lloyds Banking Group plc. Data availability is given for 2006, 2007, and 2008 to compute DD and PD series. LR series is, again, computed at individual bank level during the sample period. Furthermore, the German Comdirect Bank AG is owned by the Commerzbank AG, and the German DAB Bank AG by the Unicredit Bank AG. In these two cases, all data is computed at individual bank level while general data is collected at consolidated level. Further details can be gathered from annual reports of each bank in the respective year.

The full list of banks and other related methodological notes are presented in Table 3.3. In addition to the bank name and home country, the ISIN Code and Datastream (DS) Mnemonic is listed. Furthermore, the currency is listed to show that some currency in annual reports differ from the local currency. Balance sheet data, needed in order to calculate the LR and financial soundness measures, for each individual bank is retrieved from annual reports which are published under the rubric investor relations on the corresponding website of the banks. Regarding accounting data, consolidated financial statements are utilized except for the cases mentioned above. This approach has been adopted due to the often unavailability of unconsolidated financial statements data. One reason is that banks are often de-listed when holding companies are listed instead. Market data, needed only for the calibration purposes of the financial soundness measures, is obtained from Thomson Reuters Datastream and Eikon.

	Bank Name	Country	ISIN Code	DS Mnemonic	Currency
1	Commerzbank AG	Germany	DE000CBK1001	D:CBK	EUR
2	Deutsche Bank AG	Germany	DE0005140008	D:DBK	EUR
3	Deutsche Postbank AG	Germany	DE0008001009	D:DPB	EUR
4	Concord Investmentbank AG	Germany	DE0005410203	D:CEF	EUR
5	Comdirect Bank AG	Germany	DE0005428007	D:COM	EUR
6	DAB Bank AG	Germany	DE0005072300	D:DRN	EUR
7	Landesbank Berlin AG	Germany	DE0008023227	D:BEB2	EUR
8	National Bank of Greece	Greece	GRS003013000	G:ETE	EUR
9	Bank of Ireland	Ireland	IE0030606259	BKIR	EUR
10	ALLIED IRISH BANKS Plc	Ireland	IE0000197834	ALBK	EUR
11	PKO BP	Poland	PLPKO0000016	PO:PKB	**EUR**
12	Banco Santander Central Hispano	Spain	ES0113900J37	E:SCH	EUR
13	BBVA SA	Spain	ES0113211835	E:BBVA	EUR
14	Banco Espanol de Crédito SA	Spain	ES0113059002	E:OPCJ	EUR
15	Bankinter	Spain	ES0113679I37	E:BKT	EUR
16	Banco Popular Espanol SA	Spain	ES0113790531	E:POP	EUR
17	UBI Banca	Italy	IT0003487029	I:UBI	EUR
18	Banca Intesa SanPaolo-IMI	Italy	IT0000072618	I:ISP	EUR
19	UniCredit Italiano	Italy	IT0004781412	I:UCG	EUR
20	BNP Paribas	France	FR0000131104	F:BNP	EUR
21	Société Générale	France	FR0000130809	F:SGE	EUR
22	Natixis	France	FR0000120685	F:KN@F	EUR
23	Crédit Agricole S.A.	France	FR0000045072	F:CRDA	EUR
24	ING Groep	Netherlands	NL0000303600	H:ING	EUR
25	ABN Amro Holding NV	Netherlands	NL0000301109	H:AAB	EUR
26	Kas Bank NV	Netherlands	NL0000362648	H:KAS	EUR
27	Dexia Banque	Belgium	BE0003796134	B:DEX	EUR
28	KBC Group NV	Belgium	BE0003565737	B:KB	EUR
29	BKS Bank AG	Austria	AT0000624705	O:KAER	EUR
30	Erste Group Bank AG	Austria	AT0000652011	O:ERS	EUR
31	Raiffeisen Bank International	Austria	AT0000606306	O:RAI	EUR
32	Oberbank AG	Austria	AT0000625108	O:OBER	EUR
33	Pohjola Bank Plc	Finland	FI0009003222	M:POH	EUR
34	Barclays	UK	GB0031348658	BARC	GBP
35	Lloyds Banking Group	UK	GB0008706128	LLOY	GBP
36	HSBC Holdings Plc	UK	GB0005405286	HSBA	**USD**
37	HBOS Plc	UK	GB0030587504	HBOS	GBP
38	Standard Chartered Plc	UK	GB0004082847	STAN	**USD**
39	Schroders Plc	UK	GB0002405495	SDR	GBP
40	Royal Bank of Scotland	UK	GB00B7T77214	RBS	GBP
41	Jyske Bank A/S	Denmark	DK0010307958	DK:JYS	DKK
42	Danske Bank A/S	Denmark	DK0010274414	DK:DAB	DKK
43	Svenska Handelsbanken	Sweden	SE0000193120	W:SVK	SEK
44	Swedbank AG	Sweden	SE0000242455	W:SWED	SEK
45	Nordea Bank AB	Sweden	SE0000427361	W:NDA	**EUR**
46	UBS	Switzerland	CH0024899483	S:UBSN	CHF
47	Credit Suisse	Switzerland	CH0012138530	S:CSGN	CHF
48	Bank of America Corp	US	US0605051046	U:BAC	USD
49	Citigroup Inc	US	US1729674242	U:C	USD
50	Morgan Stanley	US	US6174464486	U:MS	USD
51	Wells Fargo	US	US9497461015	U:WFC	USD

Table 3.3: Bank sample

Apart from the three exceptions, Concord Investmentbank, HBOS and ABN, the sample period is December 2006 to December 2011. Thus, only 48 banks are tested for the full sample period. Note that the currency of the required data of four banks, PKO BP, HSBC, Standard Chartered and Nordea Bank, differs from the domestic currency. In order to standardize the currency of market and balance sheet data, if necessary, data has been converted in the same currency as those of the published annual report of the respective bank.

3.2.2 Application of the Leverage Ratio to Banks

The computation of the LR for the 51 individual banks in the sample is reported next. The LR is calculated annually for each bank, generally, at the consolidated level over the sample period from 2006 to 2011. Four cases are exceptional: the LR is calculated at individual bank level for the German banks Comdirect Bank AG and DAB Bank AG, and due to takeovers during the sample period for the ABN Amro Holding of the Netherlands and the HBOS Plc in the UK. Data as of the balance sheet date is used. The LR applied to the sample is defined as

$$LR = \frac{Tier\,1\,Capital}{Total\,Assets}\,, \tag{3.18}$$

where $Tier\,1\,Capital$ is the reported value for core Tier 1 plus additional Tier 1 capital by the banks in their annual reports. Thus, Tier 1 capital consists of the sum of following elements:

- Common Equity,
- Additional Going Concern Equity.

The Tier 1 capital is eligible under the, at that time valid, Basel II framework with the exception of one bank. The Commerzbank AG discloses since 2009 Tier 1 capital under Basel III definitions. German banks have to exclude silent partnerships from calculating its core Tier 1 capital because in German stock corporations silent partnerships will no longer count as core Tier-1-Capital from 2013.[12] Silent partnerships which have state aid character, in the case of the Commerzbank, are accepted until 2018. $Total\,assets$ represents the reported book value of total assets by banks in their annual reports. Due to the limited availability of data, LRs are calculated only from on-balance-sheet items. This is in line with, first of all, approaches in recent literature[13], and secondly, the estimates of the introduced LR in the United States by US banks. This computation might be far from a perfect indicator for the soundness of a bank. Generally off-balance sheet items should be included, as proposed by the BCBS. Nevertheless, the aim of this analysis is to analyze possible side effects of this indicator. Excluding off-balance sheet items are not expected to impact the results significantly, but will merely lead to an increase of the denominator of the ratio, i.e. the LR would decreases slightly for the entire sample. Following this approach, results will be comparable to the Basel III monitoring exercise, using the Basel II LR as a benchmark, and to the disclosed Tier 1 LRs by the US banks.

3.2.3 Application of the Financial Soundness Measures to Banks

The structural approach to calculate the DD is described in Section 3.1.2. DD and PD series is generally calculated at consolidated level, except for the two German banks Comdirect Bank AG and DAB Bank AG. In order to apply this model, pioneered by the option pricing model by Black and Scholes (1973) and Merton (1974), to individual banks, following data needs to be retrieved: the market value of equity, equity volatility, the risk-free rate and the book value

[12] See Basel Committee (2010a) for further details.
[13] See, amongst others, Kamada and Nasu (2010).

of short- and long-term liability. By dint of these variables, the value of assets and its volatility can be estimated in a first step. A historical database is used to estimate the empirical distribution of changes in DD and to calculate the PD based on that distribution.

As observable market value of equity, V_E, the yearly average market capitalization of individual banks is employed. Daily data for the period from January 2, 2006 to December 30, 2011 is obtained from Worldscope Fundamentals, available through the Thomson Financial Datastream Database. Yearly averages based on the daily data are calculated in the same currency as those of the balance sheet data of each bank. V_E corresponds to the market value of the bank by providing a total value for the banks' outstanding shares. Datastream Datatype Definition defines market capitalization as the product of the market price year end and the common shares outstanding. The market price year end represents the closing price of the bank's stock at their fiscal year end.

The equity volatility, σ_E, is estimated by taking the standard deviation of monthly equity returns in a rolling one-year window, i.e. 12 months, over the same period as mentioned above. First of all, the monthly market price close is obtained from Worldscope, again available through Datastream and expressed in domestic currency. Datastream Datatype Definition defines the market price close as the market price of the stock at the relevant month end. The month is determined by the start date specified in the time series request, i.e. the 2nd of January. Secondly, the difference between the logarithmic prices are taken to measure the relative price changes. These differences, the so-called log-relative returns, are normally distributed and satisfy

$$Log_{relatives} = ln(price_t/price_{t-1})\,, \tag{3.19}$$

where $price_t$ is the market price close at time t and $price_{t-1}$ the market price close at time $t-1$. Finally, to express the volatility in annual terms the standard deviation of the samples series is calculated and scaled with the annualization factor $\sqrt{12}$ which is the number of intervals per annum for monthly data. The equity volatility corresponds to the historical equity volatility. Saldías (2012) argues that using historical returns data is common, if the indicator has a backward-looking specification. The financial soundness measures employed in this analysis do not necessarily need to have a forward-looking feature, but assess financial soundness of individual banks in the past. Thus, employing historical volatility seems reasonable. Further examples of this approach cited in literature are found in Bharath and Shumway (2008), Saldías (2009), Gropp et al. (2006) and Vassalou and Xing (2004).

The total liabilities, D, are obtained from the banks published annual reports and expressed in the currency as reported in Table 3.3. The book value, as of the balance sheet date, is used in this model. As risk free rates, r, which correspond to the expected rate of growth in the value of assets over the analyzed horizon, the 12 months interbank offered rates are used. They are based on estimates by leading banks and represent the averaged rates a bank would be charged if borrowing from another bank. Loans taken by the banks are generally risk free and thus, these rates are considered risk-free. In addition, Bliss and Panigirtzoglou (2004) argue that interbank offered rates are good proxies of borrowing costs because they are highly liquid and less prone to be affected by monetary policy actions. For banks in the Euro-zone plus Poland the 1 year EURIBOR is used and for all other banks the LIBOR rate denominated in the domestic currency is used: Switzerland (CHF LIBOR), United States (USD LIBOR), Denmark (DKK LIBOR), Sweden (SEK LIBOR) and United Kingdom (UK LIBOR). EURIBOR and LIBOR are primary benchmarks for short term interest rates in the world[14]. Interbank offered rates are retrieved

[14] Further details on interbank offered rates is provided by European Central Bank (2012).

from Thomson Financial Datastream Database on a daily basis for the period of January 2, 2006 to December 30, 2011. In a second step, the continuously compounded rate is calculated

$$r = ln(1 + R)\,, \tag{3.20}$$

where r is the continuously compounded risk free rate and R the simple interest rate. Finally, yearly average rates are computed for each bank. The 12 months rate is chosen because it fits the time horizon of the DD, i.e. corresponds to period T, the assumed maturity of debt in this model. Hence, the time horizon for the maturity of debt, T, is set to one year. Vulpes and Brasili (2006) and Bharath and Shumway (2008) argue that this is a common benchmark assumption due to two reasons: first of all, specific information about the maturity structure of liabilities is not available, and secondly, annual default probabilities are of interest for further research purposes.

Once retrieved, the required data, V_E, σ_E, D, r and T, estimates of the value of assets and asset volatility can be computed by solving backwards the Equations (3.4) and (3.9). The technical computing software Wolfram Mathematica 8 is applied and uses a complex iterative procedure to solve asset value and volatility. An initial guess is used by the procedure to estimate the asset value and to de-lever the equity returns. As the input of the second iteration of the procedure, the volatility of the resulting returns on asset is used. A new set of asset values and thus a new series of asset returns is determined. The iterative procedure continues in this manner until it converges. Yearly estimates of the value of assets and its volatility are obtained in order to calculate the DD for the individual bank in a second step. The DD is derived from Equation (3.13). The DD is expressed in the number of standard deviations of annual asset growth by which the expected asset value at the fixed time horizon of 1 year exceeds

Variable		Definition	Source
(V_E)	Market Value of Equity	Yearly average equity market capitalization	Worldscope, code WC08001
(σ_E)	Equity volatility	Annualized standard deviation of monthly absolute equity returns	Worldscope, code WCP
(D)	Book value of liabilities	Total liabilities at balance sheet date	As reported in Annual Reports
(r)	Risk free rate	Interbank Offered Rate 12 months for each currency	Thomson Datastream codes: Euro-zone (EIBOR1Y), UK (BBGBP12), Denmark (BBDKK12), US (BBUSD12), Sweden (BBSEK12), Switzerland (BBCHF12)
(T)	Time horizon	Fixed at one year	
(V_A)	Market value of assets	Derived (equation (3.4)) yearly average of the total asset value	Wolfram Mathematica 8
(σ_A)	Asset volatility	Derived (equation (3.9)) yearly estimate of the asset value volatility	Wolfram Mathematica 8
(DD)	Distance to Default	Derived (equation (3.13) yearly average DD	Own calculations
(PD)	Probability of Default	Derived (equation (3.17) PD within one year	Own calculations

Table 3.4: Description of Variables

the default point. Once the DD for each bank in the sample has been obtained, the PD is derived from Equation (3.17) respectively. The PD determines the probability that a bank defaults within the next year. Table 3.4 summarizes all variables, their definition and the source of data.

3.3 Results

This section reports empirical results of the calibration of the LR and financial soundness measures series. Again, this section starts off with the LR series and is followed by results for the DD and PD series. Furthermore, results are discussed and related to extraordinary events during the observation period such as the global financial crisis.

3.3.1 Leverage Ratio Series

The capitalization of the banking system can be monitored by evaluating the empirical findings regarding the LR. First of all, overall results for the entire sample are discussed. Then, results for individual banks are presented and interpreted. Table 3.5 provides summary statistics for the non risk-based regulatory measure. The number of observations is only 50 after 2008 due to the bankruptcy of the Concord Investmentbank in the same year, see Section 3.2.1. Turning to the minimum LRs observed in each year, it can be seen that the

	LR (%)					
	2011	2010	2009	2008	2007	2006
Mean	4.83	4.64	4.65	3.98	4.65	5.03
Median	4.48	4.33	4.34	3.78	3.58	3.73
Max.	11.02	10.00	10.62	8.07	40.74	48.48
Min.	1.53	2.22	2.04	1.41	1.47	1.34
Std. Dev.	1.97	1.84	1.88	1.68	5.43	6.51
Obs.	50	50	50	50	51	51

Table 3.5: Summary statistics LR

minimum ratio did not change dramatically over years. A small upsurge can be observed in year 2009 and 2010. Still, it can be seen that during the entire sample period, there are banks that did not meet the calibration target of 3%, even though, off-balance sheet items are excluded and Tier 1 capital is defined as eligible Tier 1 capital under Basel II. Including off-balance sheet items and applying Basel III Tier 1 capital definition would further reduce the LRs dramatically. The maximum LRs are observed in 2007 and 2006. These two values are misleading because they are entirely exceptional. The LRs belong to the bankrupt German bank Concord Investmentbank AG. Otherwise, the highest LR of an individual bank is monitored in 2011 at 11.2%. The observed maximum values demonstrate that some banks seem to be very well capitalized over the sample period. The 3% requirement does not pose any difficulty in these cases. The average LR, mean, started at its highest level in 2006 at 5.03%, dropped by about 1% until 2008 and increased again until 2011, finally reaching a level of 4.83%. The median shows a similar trend. During the period from 2006 to 2008, the median was at relatively stable levels. An increase of about 0.5% was observed from 2008 to 2009. After that the median of the LR stayed at levels of around 4.4%. The median seems more suitable to analyze the capitalization of the banking sector, because it is less affected by outliners, e.g. the Concord Investmentbank. Overall, it can be concluded that mean and median increased in year 2009 and banks possessed a higher LR during the second half of the sample period, from 2009 to 2011. According to the mean and median, the banks in the sample meet the 3% LR level and can be considered adequately capitalized at least under the Basel II Tier 1 capital definition. The standard deviation shows steady levels for year 2008 to 2011. Movements of the standard deviation in year 2006 and 2007 can be explained due to the enormously high LR of the Concord Investmentbank, bank number three, which can be seen clearly in Figure 3.4. This results in a higher variance of the values.

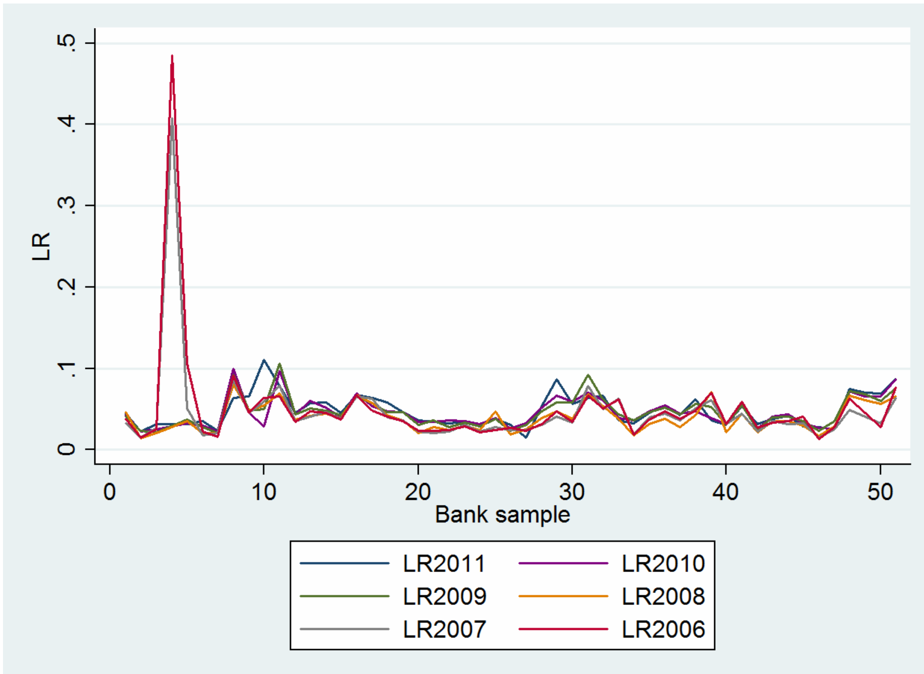

Figure 3.4: LR graphed by years overlaid

In view of the financial crisis, it can be concluded that on average the LR increased in the years after the breakout of the crisis in 2008, indicating that banks were on average better capitalized during and after the crisis than before. Whether there is a statistically significant relationship between the financial crisis in terms of increased vulnerability of the banking system and increased LRs remains to be seen. Another reason could be that banks are already preparing for higher capital requirements to come in 2013.

In order to compare the empirical results with the Basel III monitoring exercise, Table 3.6 summarizes average empirical findings for German banks only, at European and world level for the year 2011. Results of the Basel III monitoring exercise are stated in parenthesis. Note that the Basel II LR is compared and not the Basel III LR. The mean for German banks includes 5

German banks. Adding all other countries in Europe, leads to a sample of 46 at European level. The World level is equal to the entire sample as stated before. Additionally four US banks are included, adding up to 50 banks in the sample of 2011. The results of the monitoring exercise are lower, but only slightly. It can be seen, that our own calculations are appropriate and show the same trend as the studies commissioned by the BCBS. Lowest levels of the LR are observed on average in Germany. At European level the ratio improves and reaches its high at World level. In contrast to the monitoring exercise, off-balance sheet items are not included in these calculations. This explains the slightly higher values. As a result, off-balance sheet items do not seem to have a significant impact on calculating the LR.

2011	Mean LR (%)
European level	4.59 *(4.1)*
World level	4.83 *(4.4)*
Germany	3.14 *(3.0)*

Table 3.6: Results for German banks, at European and World level

Next, results regarding the LR are provided for each bank. Some cases which stand out are discussed in detail. Table 3.7 shows the LRs for individual banks. It can be seen that, overall, the fluctuation within the levels of each bank during the sample period was not strong. If there are any differences at individual bank level over the years, usually, the change was within one or two capitalization categories, see Table 3.1. An exception is the Irish bank Allied Irish Banks. The ratio continued to decline throughout its history from 2006 to 2010, and sharply increased by almost 8% in 2011. High fluctuations may result from the Irish Banking crisis which will be discussed in the next Section 3.3.2. The bankrupt Concord Investmentbank AG displayed the highest LRs observed for the entire sample in year 2006 and 2007. Insolvency was filed in February 2009. Thus, the German bank became insolvent in 2008. LRs in previous years do not give any hints that the bank is critically capitalized. As discussed before, a LR restriction has been in place in the United States since 2007. LR are disclosed in the annual reports by US banks. The published ratios are reported in Table 3.7 as well. They are stated in parenthesis next to the calculated LRs for US banks. Note that slight differences are due to the different definition of the denominator. The US banks use adjusted quarterly average total assets[15]. Comparing own calculations to the disclosed ratios by the banks themselves, proves that the calibration of the LR is appropriate and in line with US standards.

Regarding the 3% calibration target of the LR, it can be concluded, that four out of six German banks, two out of three Dutch banks, the two Swiss banks and the Danish bank Danske struggled most of the time to reach the benchmark. Furthermore, findings on the LR demonstrate that there is a significant variation in their levels across countries. For example, banks in Germany (the Concord Investmentbank is excluded), France and Switzerland had relatively low LRs. The average LR of the entire sample period for these three countries was less than 3% (Germany 2.3%, Switzerland 2.43% and France 2.93%). All three countries struggled to meet the 3% calibration target and will need to increase their Tier 1 capital extremely to achieve the benchmark level under Basel III conditions. This group of countries with very low LRs is followed by the United Kingdom, Spain and Italy with an average LR of 4.15%, 4.92% and 4.81% respectively. It can be expected that, overall, banks in these countries will meet the 3% target under Basel III conditions before the framework will be fully phased in. The peak group is presented by the United States and Austria with an average LR of 6.35% and 5.88% respectively. LRs of these banks were high compared to the European countries. Table 3.8 summarizes the results. Findings are in line with the results of the empirical analysis by Morris and Shin (2008) and Kamada and Nasu (2010). Kamada and Nasu (2010) argue

[15]See Federal Deposit Insurance Corporation (2011) for the definition of the US LR.

LR (%)	2011	2010	2009	2008	2007	2006
Commerzbank AG	4.43	4.29	4.09	4.63	3.24	3.77
Deutsche Bank AG	2.27	2.23	2.29	1.14	1.47	1.55
Deutsche Postbank AG	3.20	2.51	2.16	2.09	2.69	2.54
Concord Investmentbank AG	NA	NA	NA	NA	40.74	48.48
Comdirect Bank AG	3.13	3.22	3.68	3.50	5.10	10.62
DAB Bank AG	3.49	2.97	2.76	2.09	1.77	2.20
Landesbank Berlin AG	2.32	2.22	2.04	2.09	2.03	1.63
National Bank of Greece	6.38	10.00	9.21	8.07	8.58	9.14
Bank of Ireland	6.53	4.58	4.85	4.77	4.55	4.50
ALLIED IRISH BANKS Plc	11.02	2.92	4.97	5.45	5.90	6.38
PKO BP	7.87	9.66	10.62	6.90	7.82	6.53
Banco Santander Central Hispano	4.53	4.37	4.36	3.71	3.53	3.39
BBVA SA	5.72	5.97	5.09	4.19	4.12	4.76
Banco Espanol de Crédito SA	5.83	5.15	4.85	4.48	4.59	4.56
Bankinter	4.53	3.96	4.22	3.93	3.83	3.69
Banco Popular Espanol SA	6.76	6.97	6.54	6.77	6.57	6.75
UBI Banca	6.38	5.40	5.69	5.69	6.33	4.82
Banca Intesa SanPaolo-IMI	5.83	4.73	4.63	4.26	4.01	4.10
UniCredit Italiano	4.63	4.63	4.62	3.62	3.58	3.57
BNP Paribas	3.62	3.43	3.06	2.01	2.22	2.31
Société Générale	3.39	3.44	3.61	2.81	2.02	2.33
Natixis	3.25	3.65	2.83	2.41	2.25	2.44
Crédit Agricole S.A.	3.46	3.54	3.37	3.02	3.03	2.92
ING Groep	3.02	3.15	2.92	2.40	2.27	2.10
ABN Amro Holding NV	3.79	3.93	3.78	4.68	2.81	2.41
Kas Bank NV	3.07	2.61	2.29	1.92	2.41	2.74
Dexia Banque	1.53	3.25	3.03	2.47	2.41	2.29
KBC Group NV	5.33	5.21	4.75	3.88	3.07	3.20
BKS Bank AG	8.66	6.68	5.86	4.72	4.10	4.70
Erste Group Bank AG	5.67	5.94	5.79	3.79	3.33	3.40
Raiffeisen Bank International	6.42	7.01	9.27	6.86	7.82	6.64
Oberbank AG	6.68	6.14	6.21	5.39	5.02	5.07
Pohjola Bank Plc	3.61	9.92	4.33	3.80	6.26	6.21
Barclays	3.23	3.60	3.60	1.81	1.87	1.86
Lloyds Banking Group	4.53	4.75	4.63	3.14	3.95	3.73
HSBC Holdings Plc	5.46	5.43	5.17	3.77	4.46	4.72
HBOS Plc	4.30	4.49	4.31	2.81	3.66	3.79
Standard Chartered Plc	6.18	4.70	5.63	4.31	5.10	4.78
Schroders Plc	3.61	3.93	5.26	7.14	6.06	6.99
Royal Bank of Scotland	3.05	3.18	3.06	2.18	3.11	3.14
Jyske Bank A/S	5.33	5.86	5.45	4.14	4.40	5.89
Danske Bank A/S	3.12	2.64	2.55	2.18	2.20	2.70
Svenska Handelsbanken	3.81	4.08	4.03	3.51	3.53	3.31
Swedbank AG	4.16	4.40	4.04	3.56	3.17	3.51
Nordea Bank AB	2.89	3.29	3.50	3.02	3.30	4.09
UBS	2.75	2.68	2.37	1.65	1.50	1.34
Credit Suisse	2.47	2.58	3.51	2.92	2.55	2.80
Bank of America Corp	7.48 *(7.53)*	7.23 *(7.21)*	7.21 *(6.88)*	6.64 *(6.4)*	4.86 *(5.0)*	6.24 *(5.9)*
Citigroup Inc	7.04 *(7.2)*	6.59 *(6.6)*	6.84 *(6.9)*	6.13 *(6.1)*	4.08 *(4.0)*	5.21 *(5.2)*
Morgan Stanley	6.97 *(6.8)*	6.54 *(6.6)*	6.05 *(5.8)*	5.60 *(6.6)*	3.29 *(3.1)*	2.83 *(3.2)*
Wells Fargo	8.67 *(9.0)*	8.69 *(9.12)*	7.54 *(7.9)*	6.60 *(6.3)*	6.38 *(6.8)*	7.63 *(7.9)*

Table 3.7: LR per Bank

Country	Mean LR (%)
Germany	2.3
Switzerland	2.4
France	2.9
UK	4.2
Spain	4.9
Italy	4.8
US	6.4
Austria	5.9

Table 3.8: Average LR per country

that in the United States the LRs are high because a constraint on leverage was put in place. Morris and Shin (2008) explain that another reason could be the differences between the IFRS and US GAAP accounting regimes. IFRS results in higher total asset amounts, and thus lower LRs for similar exposures, than does the use of US GAAP. The reason arises from stricter netting conditions using IFRS, showing gross replacement value of derivatives on the balance sheet. As discussed before, the United States was at the epicenter of the financial crisis despite already having a LR in place during the financial crisis. After discussing the empirical results for the US banks in the sample, the question remains why the LR failed to provide warning signs. One possible reason could be that the LR does not reflect every type of leverage. During the period of crisis leverage was assumed through economic leverage, see Section 2.2. This type is not recorded on the balance sheet. Thus, including off-balance sheet items could improve the predictive power of the LR. However, the investigation and comparison of the results of the monitoring exercise has shown that off-balance sheet items supposedly do not improve significantly the signaling effect of the LR. In addition, the build-up of funding liquidity risk contributed to a great extension to the crisis. These risks are not captured by the LR. It can be concluded that the extent of leverage accumulated over the last several years in the financial system has only recently become visible. Morris and Shin (2008), further, conclude that a constraint on leverage seems particularly appropriate for Switzerland because UBS and Credit Suisse were both highly leveraged in 2007. This statement can be confirmed. The total assets of UBS at the end of 2006 were 2.4 trillion Swiss francs. With the Tier 1 capital of 32 billion Swiss francs, this implies a LR of only 1.34%. The relation improved slightly in 2011. Total assets decreased to 1.4 trillion Swiss francs and Tier 1 capital increased slightly by 7 billion Swiss francs which resulted in a higher LR of 2.75%. It could be argued that the introduction of a minimum LR of 3% solely for Credit Suisse and UBS, see Section 3.1.1, is the reason for the increasing LRs recently. Nevertheless, neither UBS nor Credit Suisse met the calibration target of 3%. Credit Suisse only once fulfilled the LR criteria with a LR of 3.51% in 2009.

To sum up, capital capitalization of banks in the dataset varies considerably and making an overall final statement regarding financial risk in the banking sector is difficult. Still, the majority of the banks in the sample met the 3% calibration target of the LR at that point of time. Only a few were below the 3% level. Germany, Switzerland and the Netherlands especially seem to struggle enormously to meet the 3% LR level. Applying the definition of Tier 1 capital under the Basel III agreement, would probably result in the majority of banks having trouble meeting the 3% level. Still, there is time to adjust to the new capital requirement because the Basel III LR will not be fully phased-in until 2018. In addition, LRs on average increased after the the outbreak of the financial crisis, from 2009 to 2011 (see, amongst others, Barclays and BNP Paribas). The panel data analysis in Chapter 4 will analyze if there is a correlation between the fragility of the banking sector and the LRs, or if higher LRs are due to increasing capital requirements.

3.3.2 Distance to Default and Probability of Default Series

The analyzed financial soundness measures are useful tools in monitoring systemic risk over time in the banking sector. On the basis of the DD and PD series, over the sample period from 2006 to 2011, it is possible to identify a build-up of risk in the system, while the series report quick and short-lived reactions to specific market events. The sample period includes the financial crisis 2007/2008, and thus, allows one to track systemic risk during crisis and non-crisis episodes. The crisis has to be kept in mind while interpreting the results of the financial soundness measures analysis. Summary statistics of the DDs and PDs for each year of the sample period are reported in Table 3.9. The number of observations varies across the sample period. The Concord Investmentbank and ABN are included only for years 2006 and 2007. Further, HBOS is included for years 2006 to 2008. For details see Section 3.2.1. In 2011, three US banks were not tested due to non-availability of data at the time of the data collection. Note that the minimum value of the PD is zero, i.e. the probability that the market value of assets declines to the bank specific default barrier within the given time horizon of one year is zero. Thus, banks with a PD of zero display no signs of bank distress within the next year and can be considered as stable and sound. In this case, the DD of the bank can help to make a more precise and explicit statement regarding the bank's soundness. Due to the laws of the Standard Normal Probability Distribution, Equation (3.17) and the negative relationship between the DD and PD, a DD around the value of 4 or greater converges to a PD of zero. In every year the PD series reports at least one bank with a PD of zero. In turn, a DD of zero results in a PD of 0.5. In Table 3.9 it can be seen that in years 2009 and 2011 at least one bank of the sample had a negative DD, i.e. that the value of assets is below the default point (strike).

	DD						PD (%)					
	2011	2010	2009	2008	2007	2006	2011	2010	2009	2008	2007	2006
Mean	4.57	4.08	2.55	3.70	5.24	6.78	3.77	1.32	14.51	5.69	0.11	0.11
Median	2.97	3.05	1.51	2.00	5.28	5.70	0.15	0.11	6.80	2.27	0.00	0.00
Max.	39.74	40.00	47.68	75.70	10.06	44.38	77.00	29.01	89.31	28.69	3.25	5.05
Min.	-0.44	0.55	-1.24	0.56	1.84	1.64	0	0	0	0	0	0
Std. Dev.	6.87	5.47	6.80	10.64	1.65	5.81	11.67	4.63	20.14	6.92	0.50	0.71
Obs.	45	48	48	49	51	51	45	48	48	49	51	51

Table 3.9: Summary statistics DD and PD

A negative number of standard deviations away from the bank specific default point increases the PD level in the range of 0.5 up to 1. In compliance to the negative minimum values of the DD, the highest PDs were observed in year 2009 and 2011. In addition, mean and median of every year is reported. For the financial risk analysis, again, the median seems to be more appropriate to evaluate financial risk over the sample period, because this measure of central tendency is little affected by outliers. Nevertheless, the mean and median of the DD and PD movements show the same trend. The DD series started at high levels in the years before the crisis, 2006 and 2007. Correspondingly the PDs were very low in these two years. Overall, the banking system is considered as healthy and stable during this period. The DD dropped sharply in 2008 and kept falling until 2009 where the series hit rock bottom. PD movements were the same. PD series hit its peak in 2009, also. During the years 2008 and 2009 the effects of the global financial crisis were clearly evident in the sample. The banking system was considered to be more vulnerable. On average, banks were under financial distress and bank soundness was dramatically jeopardized. In 2010 and 2011 DDs increased and PDs declined sharply. The series experienced a recovery. According to the findings, financial health improved again, even though, levels as before the financial crisis are not reached. The average DD after 2009 improved but is smaller than the average DD in 2007 and the average PD in 2010 and 2011 was slightly higher than in 2007. It seems that banks recovered from the crisis and regained its financial soundness. To sum up, vulnerability of the banking system decreased and overall soundness was enhanced.

Next, findings regarding the standard deviation of the DD and PD series during the sample period are discussed. Movements of the standard deviation are similar for both series. They fluctuated over the analyzed period. The lowest values were observed in year 2007. The standard deviation increases drastically and hit its peak in 2008 for the DD series and in 2009 for the PD series. The negative effects of the financial crisis were noticeable and led to a greater dispersion of the set of data from its mean. Banks were exposed to a turbulent banking system and responded differently to distress. Turning to the period from 2009 to 2011, the standard deviation of the DD series was more or less stable but considerably higher than in 2007. Standard deviation of the PD series dropped sharply in 2010 but increased again in 2011 and exceeded by far the standard deviation in 2006 and 2007. The European sovereign debt crisis could have played a decisive role during the second half of 2011. Overall, it can be concluded that, according to the DD and PD series, the banking system was considered as healthy and sound in year 2006 and 2007. These two years are characterized by high DDs and low PDs, as well as low standard deviations. In 2008 and 2009, effects of the global financial crisis were felt strongly. DDs declined sharply, PDs and the standard deviation increased drastically. Banks experienced financial distress which increased the fragility of the banking system as a whole. After 2009, the DD and PD series recovered but did not reach levels of the years before the financial crisis. This indicates that banks soundness enhanced and financial health improved slightly. The standard deviation exhibits a similar trend. Nevertheless, turbulence of the crisis continues to be felt and banks are exposed to new expected disruptions resulting from the European sovereign debt crisis in 2011.

After discussing results generally accepted for the entire sample, an examination of the PD per bank follows. Results are reported in Table 3.10. It is possible to detect individual banks that were particularly stable and healthy, or experienced exactly the opposite, vulnerability and financial distress. Results for most banks are consistent with the overall observable trend of the PD series:

low default probabilities in 2006 and 2007, sharply increase in 2008 or 2009 and declining PDs after 2009. A few banks, however, stand out in a positive, as well as, in a negative manner to which particular attention should be paid. Extremely high values of the PD are marked in red. Next, these cases are discussed by analyzing the reasons of these extreme values.

The first case to be analyzed is the German Commerzbank AG, which displayed a increase in its PD during the period from 2007 to 2009, where it reached a value of over 33%. This is the result of an extreme increase in its equity volatility. In 2009, the Commerzbank has had an equity volatility of around 100%. Market capitalization has dropped sharply by 72% from 2007 to 2008. In June 2009, the Commerzbank has finalized an agreement with the Financial Market Stabilization Fund (SoFFin)[16]. The Commerzbank has increased its capital by accepting an acquisition of its shares by the SoFFin. In addition, the bank received a further SoFFin silent participation. After cash injections from the German government in 2009 the bank experienced a recovery in its PD and reports very low default probabilities in 2010 and 2011.

The two Irish banks in the sample, Bank of Ireland and Allied Irish Banks, show a similar pattern of their PD series. The series started at very low levels in 2006 and 2007 or rather at the value of zero. Then PDs increased and hit their peak in 2009. In 2010, PDs declined only slightly and increased again in 2011. The market capitalization of the Bank of Ireland has dropped by 86% from 2008 to 2009 and equity volatility is above 200% in 2009 which led to a PD of almost 90% in this year. The same applies to the Allied Irish Banks which reached an equity volatility of around 150% in 2009 and 2011. Market capitalization dropped by 90% from 2007 to 2008. Both banks accepted a bailout from the government of the Republic of Ireland in 2009 to withstand the economic

[16]See Commerzbank AG (2009).

	PD (%)	2011	2010	2009	2008	2007	2006
1	Commerzbank AG	0.39	0.11	33.19	11.63	0.00	0.00
2	Deutsche Bank AG	0.87	0.42	7.46	4.86	0.00	0.00
3	Deutsche Postbank AG	0.00	0.00	14.90	12.57	0.02	0.00
4	Concord Investmentbank AG	NA	NA	NA	NA	3.25	5.05
5	Comdirect Bank AG	0.00	0.00	1.12	1.89	0.57	0.07
6	DAB Bank AG	0.00	0.00	0.83	10.24	0.17	0.00
7	Landesbank Berlin AG	0.00	0.00	0.91	0.12	0.00	0.24
8	National Bank of Greece	9.66	2.78	6.89	3.58	0.00	0.02
9	Bank of Ireland	31.57	29.01	89.31	16.16	0.00	0.00
10	ALLIED IRISH BANKS Plc	66.99	14.92	75.86	9.40	0.00	0.01
11	PKO BP	0.00	0.01	7.49	1.87	0.00	0.00
12	Banco Santander Central Hispano	0.00	0.24	2.22	0.72	0.00	0.00
13	BBVA SA	0.03	0.90	3.27	0.12	0.00	0.00
14	Banco Espanol de Crédito SA	0.00	0.36	1.74	0.01	0.02	0.00
15	Bankinter	0.03	0.28	0.37	2.27	1.47	0.00
16	Banco Popular Espanol SA	0.00	1.03	6.47	0.46	0.00	0.00
17	UBI Banca	2.13	0.72	1.13	0.01	0.00	0.00
18	Banca Intesa SanPaolo-IMI	2.63	0.59	0.62	0.75	0.00	0.00
19	UniCredit Italiano	0.82	1.19	11.67	1.86	0.00	0.00
20	BNP Paribas	0.65	0.06	0.74	2.67	0.00	0.00
21	Société Générale	2.62	2.00	4.36	5.36	0.02	0.00
22	Natixis	0.04	0.24	15.31	7.23	0.00	0.16
23	Crédit Agricole S.A.	2.11	2.24	4.70	1.25	0.00	0.00
24	ING Groep	0.50	0.06	28.56	18.89	0.00	0.00
25	ABN Amro Holding NV	NA	NA	NA	NA	0.00	0.00
26	Kas Bank NV	0.00	0.00	0.36	4.48	0.00	0.00
27	Dexia Banque	28.43	1.07	19.94	12.63	0.01	0.00
28	KBC Group NV	14.70	0.00	40.42	6.36	0.00	0.00
29	BKS Bank AG	0.00	0.00	0.00	0.00	0.00	0.00
30	Erste Group Bank AG	1.32	0.26	23.70	8.48	0.00	0.00
31	Raiffeisen Bank International	0.46	0.11	6.72	17.19	0.00	0.20
32	Oberbank AG	0.00	0.00	0.00	0.00	0.00	0.00
33	Pohjola Bank Plc	0.00	0.00	8.73	0.00	0.00	0.00
34	Barclays	1.13	0.48	28.39	8.87	0.00	0.00
35	Lloyds Banking Group	0.25	0.81	24.48	0.54	0.00	0.00
36	HSBC Holdings Plc	0.13	0.00	2.73	0.25	0.00	0.00
37	HBOS Plc	NA	NA	NA	26.22	0.00	0.00
38	Standard Chartered Plc	0.00	0.00	3.64	0.83	0.00	0.00
39	Schroders Plc	0.02	0.02	0.03	0.47	0.01	0.00
40	Royal Bank of Scotland	1.19	2.31	40.37	28.69	0.00	0.00
41	Jyske Bank A/S	0.20	0.12	3.58	2.45	0.00	0.00
42	Danske Bank A/S	0.15	0.04	16.21	1.73	0.00	0.00
43	Svenska Handelsbanken	0.00	0.00	1.98	0.00	0.00	0.00
44	Swedbank AG	0.46	0.01	18.91	1.65	0.00	0.00
45	Nordea Bank AB	0.00	0.00	2.78	0.58	0.00	0.00
46	UBS	0.05	0.21	7.82	6.34	0.00	0.00
47	Credit Suisse	0.19	0.05	0.08	0.53	0.00	0.00
48	Bank of America Corp	NA	0.22	47.67	13.13	0.00	0.00
49	Citigroup Inc	NA	0.03	59.47	11.56	0.01	0.00
50	Morgan Stanley	NA	0.08	0.35	10.06	0.05	0.00
51	Wells Fargo	0.00	0.24	18.69	2.04	0.00	0.00

Table 3.10: PD per Bank

downturn, especially the impact of a deteriorating credit environment[17]. Government re-capitalization package enabled the banks to strengthen their capital position. PDs decreased slightly in 2010 from their high in 2009, but increased again dramatically in 2011. According to the PDs of these two banks, the Irish banking crisis seems to continue until today.

The Belgian bank Dexia Banque showed a high PD in 2009 of almost 20% and its highest value of around 28% in 2011. Dexia accepted a bailout from the Belgian government in 2008 which helped to recover rapidly[18]. The PD dropped sharply from 2009 to 2010. Nevertheless, it seems like that the bank has not been able to get the burden of the financial crisis under control. The bank experienced a drop in its value by almost 88% and an increase in equity volatility by 53% from 2010 to 2011. Dexia Banque (2011) argues that the bank struggled due to the worsening of the European sovereign debt crisis and the disruptions to the financial markets involved. In 2011 a breakup took place when some units were purchased by the Belgian federal government.

The Royal Bank of Scotland reached its highest PD in 2009 (40%). Equity volatility in this year was about 110%. In addition, the bank experienced a drop in its value by 56% from 2007 to 2008. The bank has accepted a bailout from the British government in 2008. The CEO states in a company announcement from October 8th, 2008 that the bank welcomes the comprehensive package from the government in order to enhance its soundness and to ensure the stability of the financial system[19]. In February 2009, 68% of the shares were owned by the UK government. Accordingly, the PDs in 2010 and 2011 improved.

The Bank of America possessed a high PD of almost 48% in 2009 due to an equity volatility of around 120% in this year. The value of the bank declined by

[17]Further details on the government bailout are provided by the banks themselves, see Bank of Ireland (2009) or Allied Irish Banks (2009).

[18]See Dexia Banque (2008).

[19]See The Royal Bank of Scotland Group PLC (2008).

61% from 2007 to 2008. In addition, the Bank of America acquired Merrill Lynch in 2008 and revealed massive losses at this bank in its 2009 earning release[20]. After this announcement, the stock price dropped to its lowest levels in 17 years. Obviously financial health in terms of default probabilites of this bank improved in 2010. The American bank Citigroup Inc displayed a PD of almost 60% in 2009 and possessed an equity volatility of 140% in this year. They suffered huge losses during the financial crisis and had to be rescued in November 2008 by the US government[21]. To sum up, estimates of the PDs are in line with the

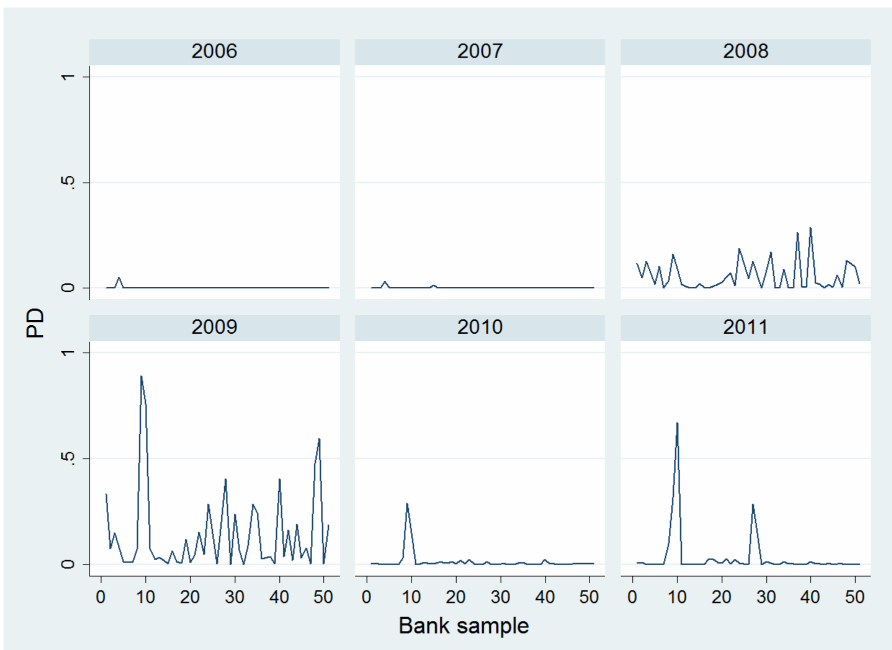

Figure 3.5: PD graphed by year

facts depicted by each bank. Some banks would probably have defaulted but for government bailouts. Figure 3.5 which shows the PD of individual banks graphed by year, displays clearly the addressed individual cases. The number of each bank can be found in Table 3.10. The shape of the plots for the Irish banks,

[20]See Bank of America (2009).
[21]See Citigroup (2008).

number 9 and 10, during the period of 2009 until 2011 is striking. Once again, Figure 3.6 shows the PD of all banks in the sample but this time curves are overlaid. The figures represent clearly the described overall results. The highest PDs were observed in 2009 followed by the year 2008. Highest variability of the data was given in these two years, also.

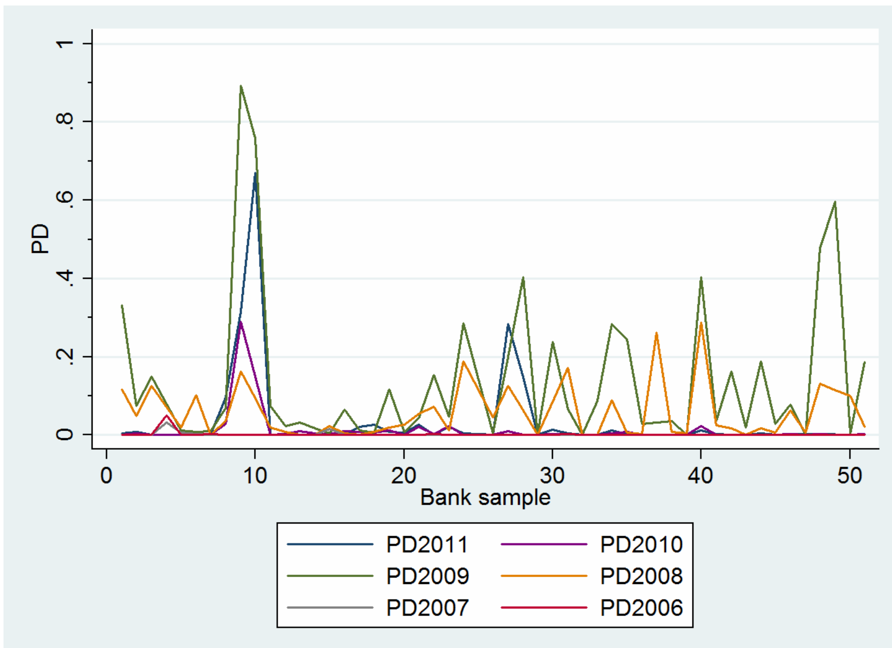

Figure 3.6: PD graphed by years overlaid

In contrast, there are some banks which had a PD of zero or near zero during the entire sample period. The Austrian banks, BKS Bank AG and Oberbank AG, performed best, closely followed by the UK bank Schroeders Plc. The financial crisis does not seem to have affected these banks negatively. The banks show low PDs while steering their way through the financial crisis. The market capitalization was more or less stable during the sample period and the equity volatility relatively low compared to other banks. During the sample period the Oberbank AG has had an equity volatility of less than 10%, BKS Bank less than 17% and Schroders less than 30%, except in 2008, the bank displayed 38% which explains the slight increase in PD from 2007 to 2008.

3.4 Conclusion

Two individual measures are applied to analyze financial risk in the banking sector. Firstly, the LRs and secondly, the DDs and PDs are computed for all banks in the sample over the period from 2006-2011. Findings regarding the LR demonstrate that the capitalization level of banks varies considerably. Furthermore, higher LRs are observed on average in the years after the financial crisis. During the sample period, the majority of banks are adequately capitalized regarding the calibration target of 3%. Certainly, banks need to further increase their capital in order to fulfill the requirement of 3% under fully phased-in Basel III Tier 1 capital definition. The case of the German Concord Investmentbank AG is striking: the bank displayed very high LRs in years right before bankruptcy. LRs did not show any sign of critical capitalization. Though, LRs are highly questionable because they are unduly high. The results for the LR demonstrate significant variation in their levels, and thus may be driven by country effects or differences in the accounting regimes across countries.

Findings regarding the PD show clearly that the highest PDs are observed during the period of the global financial crisis in year 2008 and 2009. Financial distress is very high at individual bank level which contributes to increasing bank fragility and finally to a very vulnerable banking system. After 2009, financial health improved slightly but seems to be affected again in 2011 by the European sovereign debt crisis. Disruptions to the financial markets in 2011 are clearly observable. Merging the results regarding the LR and the financial soundness measures, the following can be concluded. Even though a LR requirement had already been in place in the United States, and LRs were at very high levels compared to European banks, US banks displayed comparably high PDs during the crisis. It seems that high LRs did not protect banks from being affected by the negative impacts of the financial crisis. Another example is the Allied Irish Banks bank. This Irish bank possessed averagely high LRs and high PDs. Years 2009 and 2011 are especially striking. German and Swiss banks are in contrast to banks with high LRs and high PDs. On average, these banks displayed very low LRs, the lowest of all banks in the sample, and possessed very low PDs even during the period of 2008- 2009. It can be assumed that a nexus between these two indicators exists. Otherwise, a closer look at the Austrian banks do not confirm this assumption. These banks had relatively high LRs, directly following the US banks, but performed best during the entire sample period according to the PDs. An example for a sound banking system is Austria where a good capitalization level, due to the LR requirement, ensures banks soundness. Nevertheless, these cases are entirely exceptional in the sample and even an increase of the LR in the year of and after the financial crisis is observable.

A second analysis, a statistical panel data regression, is implemented to depict possible reasons for the findings of the financial risk analysis and to link the regulatory measure to the financial soundness measure, the PD.

Chapter 4

Panel Data Analysis

The previous chapter investigated financial risk in the banking sector by using, on the one hand, a regulatory measure and, on the other, an indicator for financial fragility. A closer look at the performance of individual banks suggests that a nexus between the LR requirement and the proxy for financial stability, the PD may exist. For instance, it is observed that banks with very high LRs possess very high PDs at the same point of time. Firstly, this chapter analyzes a possible relationship between these two measures by estimating a panel data regression model, Model 1. Furthermore, reasons for the findings derived from Model 1, either a positive or a negative relationship between the LR and PD, are examined. Thus, the focus of this research is not only on the direct relationship between these two measures, but also on the side effects of the LR and their impact on global financial stability. To detect possible side effects, a second regression model, Model 2, is employed. Results are discussed distinguishing between the micro prudential and macro prudential dimension. Finally, conclusions are drawn by applying Stiglitz and Weiss (1981) framework.

The chapter is structured as follows. Section 4.1 presents the proposed empirical methodology to base the theory and derive a conclusion. Further, three hypotheses are developed which are directly related to the research questions. In Section 4.2, two multiple linear regression models using panel data are estimated. The first model tests the first suggested hypothesis while the second model tests research hypotheses two and three. Further, descriptive statistics are presented in this section. Section 4.3 briefly reports regression diagnostics and Section 4.4 presents empirical results independently for Model 1 and 2. Finally, in Section 4.5, robustness of empirical results is investigated.

4.1 Empirical Methodology and Hypotheses

This chapter analyzes empirically the nexus between the profitability (levels of net interest margins), a bank's use of debt and financial soundness. This section provides the empirical methodology and suggested hypotheses which represent the research questions. The empirical analysis focuses on 51 stock-listed financial intermediaries across 16 countries over the period from 2006 to 2011. In-depth description of the dataset is given in Section 3.2.1.

As discussed before, in Section 3.1.1, the purpose of introducing the LR is to limit the level of a bank's debt. More precisely, a bank's equity can be leveraged only up to 33 times. The BCBS addresses this issue in order to restrain excess leverage which might have contributed to the global banking crisis[1]. Each financial institutions which does not meet the requirement needs to increase the level of Tier 1 capital. The LR is introduced to promote essentially each individual's soundness. By providing a minimum of regulatory capital in the future, irrespective to the risk in a bank, risks to the banking system as a whole are reduced. Amongst others, Blum (2008) supports the idea of supervisors. He argues that this risk-independent LR reduces incentives of banks to misrepresent

[1] See Basel Committee (2009).

their risk and that it helps to increase the bank's net worth. Overall, regulatory intention of the proposed constraint aims to promote greater resilience of the global banking system. It can be concluded that supervisors presume a positive relationship between a bank's level of debt and its soundness. Figure 4.1 reflects the intention by the supervisors. Following this line of reasoning, firstly, it is investigated, if banks with a high LR (low level of debt) are more stable and sound than financial institutions with a lower LR (higher level of debt). Still, financial stability is defined in terms of the PD of each institution, i.e. the lower a bank's PD, the better its soundness. Thus, a negative relationship between the value of the LR and the PD is expected by supervisors. The following main hypothesis is put forward:

H1: The higher a bank's leverage ratio, the lower its probability of default.

Imposing a non-risk LR does also encounter negative feedback and has been criticized in literature. Considerable negative impacts on banks' business activity as a consequence of a minimum capital ratio are widely discussed. When these effects are counter-productive to overall financial stability, they display a trade-off against the intended positive effects of the regulatory measure. As a result, critics, e.g. Hakura and Cosimano (2011) and Kiema and Jokivuolle (2011), argue that this regulatory requirement does not enhance financial stability but increases fragility. Theoretical and empirical perspectives on side-effects are given in the literature review, see Section 2.3. Following this line of argumentation, a rejection of the first hypothesis is expected. In this case, causes need to be detected and examined to verify the arguments brought forward by critics. Another hypothesis is suggested to provide information on possible disadvantages of introducing a ratio to limit a bank's level of debt. In order to discuss empirical results, the empirical methodology is embedded in the theoretical framework by Stiglitz and Weiss (1981), see Section 2.1.2 for a discussion.

Their model can be seen as an explanatory approach why possible side-effects of the LR result in a destabilizing banking sector.

Introducing this risk-independent requirement can breed undesirable incentives. The most alarming side-effect discussed in literature which possibly leads to a rejection of H1, is investigated: does the LR requirement impact loan interest rates and as a consequence banks profitability? The line of argumentation respective to this relationship is multifaceted. Often discussed in literature is the loan pricing implications of Basel II[2]. This thesis picks up some ends of Basel II research and tries to examine these effects for the LR constraint under Basel III. Stiglitz and Weiss (1981) discuss possible implications of this side effect on a bank's soundness. To analyze the direct link between the LR and banks profitability following line of argumentation is followed in this thesis, see Figure 4.2:

1. It is expected that banks pass on the additional costs, implied by increasing regulatory capital, to their borrowers via higher loan rates.
2. It is assumed that introducing the LR leads to a cut back on lending which in turn exerts immediate effects on lending interest rates.

These two reasons for an increasing bank profitability due to the LR requirement can be derived directly from the equation of the LR, see Equation (3.1). Arithmetically, an increase of the ratio can be achieved by raising the nominator (Tier 1 capital) or reducing the denominator (total assets). The former is intended by the BCBS and leads to put forward the first hypothesis. If financial institutions do not meet the LR requirement, they are supposed to increase Tier 1 capital rather than to shrink balance sheets. This is the regulatory intention of the Basel Committee (2009) of proposing this regulatory requirement, but this mindset has weaknesses. Fresh equity is not always easily accessible, and

[2]See e.g Ruthenberg and Landskroner (2008) and Repullo and Suarez (2004).

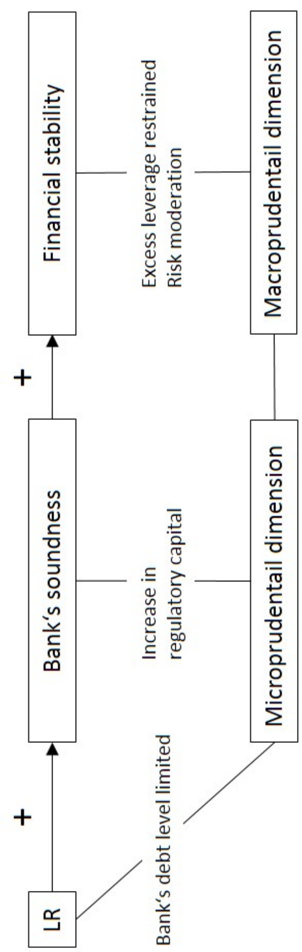

Figure 4.1: Explanatory approach of the BCBS for the positive relationship between the LR and banks' soundness

acquiring new regulatory capital can be very expensive. Gordon (1986) and Repullo and Suarez (2004) argue that factors such as taxes, agency conflicts and cost associated with the process of acquiring new equity make the regulatory capital a more expensive form of finance than debt. Thus, the marginal cost of equity increases with raising required capital. According to Hakura and Cosimano (2011), the marginal cost of loans is the weighted average of the marginal cost of equity and deposits, and will increase in equal measure. The authors give empirical evidence that higher capital requirements in general lead to higher lending rates. The fact that banks pass on these additional costs, implied by a minimum LR requirement, to their borrowers via higher loan rates is often discussed by academic researchers. Further, Demirgüç-Kunt and Huizinga (1999) give empirical evidence that there is a positive relationship between interest rates and a bank's efficiency[3]. It can be concluded, that financial institutions seek to maximize their profits by their choice of interest rate. For instance, low interest rates charged by a bank are pressing on the profit a bank earns on its lending, and the higher the loan interest rates the higher a bank's return. Thus, higher interest rates due to a minimum target of Tier 1 capital to total assets ratio implies an increasing profitability of a bank's lending activities.

The latter is a less costly approach but contrary to the intentions of supervisors. The level of regulatory capital will not be enhanced in order to comply with the 3% requirement, and the linked assumptions of a more stable banking system could be invalid. Accordingly, as a result of a LR requirement, it is conceivable that financial institutions rather decrease the value of total assets than increase the "expensive" Tier 1 capital. This is a less "costly" approach. Banks can achieve a lower value of assets by limiting their lending activity only, keeping all other assets at a constant level. This approach to generate higher

[3] Demirgüç-Kunt and Huizinga (1999), p. 380, define bank efficiency as a bank's net interest income divided by total assets which equals to the net interest margin.

LRs exerts immediate effects on interest rates. Firstly, an effect of higher interest rates on investors demand is expected on the credit market. A possible credit crunch involves that demand exceeds supply and interest rates will rise. Secondly, banks have to generate their earnings from a lower lending volume and adjust their interest related operations by raising the cost of credit. It is concluded that banks are likely to increase their charged interest rates in order to compensate the loss of earnings which are due to the cutback on lending, and to keep profit levels. In general, shrinking the balance sheet in this manner while retaining the same amount of equity, improves the LRs overall and reduces a bank's risks in its portfolio. Nevertheless, negative impacts on banks regarding the microprudential dimension can be expected. Cutting back on lending means wasting the possibility of granting loans. Profits will be decreasing while missing out on the interest a bank could earn. If interest rates are not raised, a bank will be unable to generate the same profit with lower lending. Thus, the bank's stability is not promoted. In addition, enormous macro prudential effects are anticipated. A radical cut back on lending jeopardizes credit supply to the real economy. This contraction can finally lead to a downturn. Effects on macroeconomic parameters and implications for the public sector are discussed in Thakor (1996), Basel Committee (2010a) and Angelini et al. (2011). Kashyap et al. (2010) argue that the incentive to increase a bank's LR through cutting back on lending, further raises significant concerns about credit supply activity in financial institutions. A migration of credit provision from the banking to the shadow-banking sector is expected which potentially increases the vulnerability of the financial system. This line of argumentation implies a positive relationship between the LR and a bank's profitability. Bank profitability will be proxied by a bank's net interest margin[4]. If banks profitability increases due

[4]It is assumed that banks generate higher net interest margins by increasing their loan interest rates. Further details are given in Section 4.2 and 4.4.2.

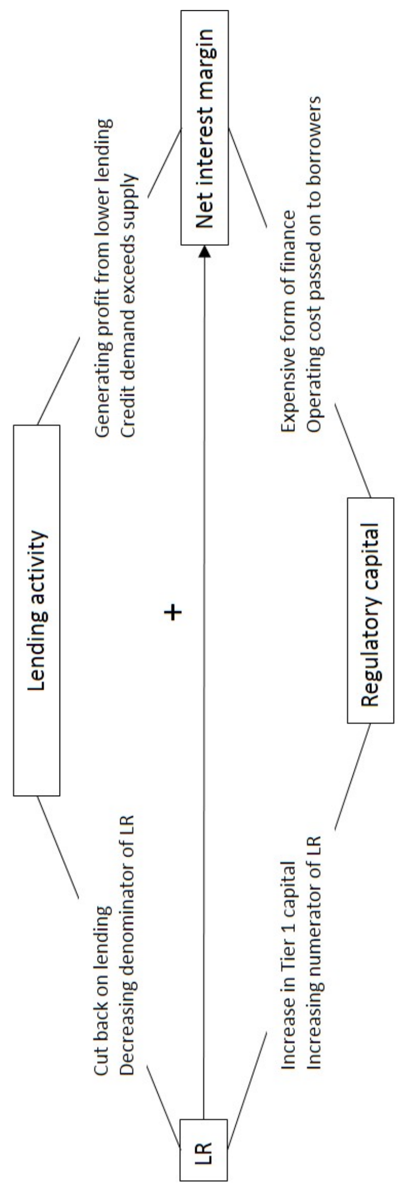

Figure 4.2: Explanatory approach for the acceptance of H2

to an increase in Tier 1 capital, an decrease in the number of loans a bank will make, or both, remains to be seen. Nevertheless, it is expected that banks will chose the less costly approach. To analyze the relationship between a bank's LR and its profitability, the following hypothesis is suggested:

H2: The profitability of a bank is positively related to its leverage ratio.

Figure 4.2 summarizes graphically the discussed side-effects which possibly lead to a rejection of H1 and provides the explanatory approach for the suggested hypotheses, H2. In contrast, Modigliani and Miller (1958) do not support this line of argumentation. The authors are certainly aware of the fact that debt-financing is "cheaper" than equity financing, but do not find empirical evidence to support this theory. Results of an employed regression analysis show that there is no significant correlation between a firm's average cost of capital and its capital structure. Note that this is valid for the basic propositions, i.e. the model does not allow for a corporate profits tax. Thus, it is concluded that the source of financing is completely independent of the cost of capital. This theorem will be monitored, also, by interpreting the regression results in Section 4.4. Stiglitz and Weiss (1981) present an explanatory approach why the acceptance of the hypothesis H2 can lead to the rejection of the hypothesis H1. A positive relationship between the LR and a bank's profitability preconditioned, their work can be considered as a tentative explanation why a LR constraint is not expected to enhance a bank's soundness. In this context, a rejection of the first hypotheses is expected and a reverse scenario is predicted: the assumption is strengthened that introducing a LR does not promote each individual's soundness but creates vulnerable financial institutions with higher default probabilities. As discussed in detail in Section 2.1.2, higher interest rates imply worse risk in a bank's loan portfolio due to the adverse selection and incentive effect. Thus, a higher concentration of risk in a bank is conceivable, which enhances vulnerability at

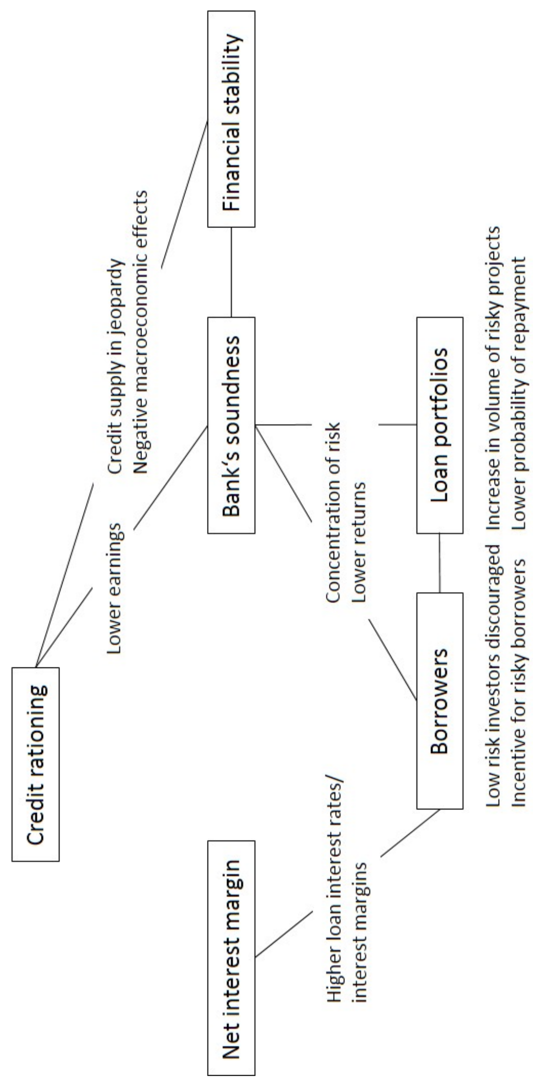

Figure 4.3: Possible side-effects of a LR and their impacts on financial stability following Stiglitz and Weiss (1981) framework

individual bank level. These indicators do not maintain a bank's soundness and result in destabilizing the financial system. Micro- and macroeconomic effects derived from the LR requirement, taking into account theoretical justification by Stiglitz and Weiss (1981), are presented in Figure 4.3.

4.2 Empirical Model and Descriptive Statistics

The next section presents the employed empirical model and descriptive statistics of the panel data. A linear regression model with panel-corrected standard errors (PCSEs) by Prais and Winsten (1954) is used. A detailed technical discussion on econometric analysis of panel data is given in Wooldridge (2010) and Baltagi (2008). Two multiple linear regression models are applied, using panel data on a sample of 51 international financial institutions and a time period of 6 years, 2006 to 2011. Detailed information on the sample is provided in Section 3.2.1. To test the first hypothesis, the higher a bank's LR, the lower its PD, the following multiple linear regression model (*Model 1*) on panel data with 291 observations is estimated

$$\begin{aligned} PD_{it} &= \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 d09_t + \gamma_4 d10_t + \gamma_5 d11_t \\ &\quad + \gamma_6 c3_i + \gamma_7 loans_{it} + \varepsilon_{it}\,, \qquad i = 1, ..., 51;\ t = 1, ..., 6\,, \end{aligned} \tag{4.1}$$

where the idiosyncratic errors satisfy

$$\varepsilon_{it} = \rho \varepsilon_{i,t-1} + u_{it},\ \mid \rho \mid < 1\,, \tag{4.2}$$

where PD_{it} represents the probability of default (PD) of bank i in a respective year t, LR_{it} the observable leverage ratio for each bank at time t. Time dummies for each year of analysis, $d07_t - d11_t$, do not change across panels but over time and are set to control time-specific effects. The year 2006 is specified as the reference category and excluded from the regression model. In addition, the model controls for country effects. As concluded in Section 3.3.2, Ireland displays the highest PDs observed over the sample period. Thus, this country could behave significantly different in the regression model than all other countries. This can distort regression results. To control this effect, a country dummy variable is added to the model, $c3_i$. The value of one is assigned to the Irish banks, all other countries are the reference category and assigned a zero.The dummy $c3_i$ does not change across time but across panels. β and γ denote the parameters to be estimated. ε_{it} is the unobservable random error which is explained in detail in Section 4.3, and β_0 is the intercept. This model is tested for including a further bank specific control variable: the total amount of loans and receivables to control for bank lending activity. A reason to include the variable *loans*, which changes across panels and time, is to combat a potential bias of the coefficient on the *LR*. Table 4.3 shows that the variable PD is correlated with the variable *loans*, i.e. there could be another factor influencing the PD other than the LR while testing the hypothesis. It can be assumed that the PD of a bank may be affected by the size of its total loans and receivables. The higher the amount of loans, the higher the PD. To test the second hypothesis, H2, that the LR requirement affects the net interest margin, another multiple linear regression model (*Model 2*) with 299 observations is estimated

$$
\begin{aligned}
IM_{it} \quad = \quad & \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 d09_t + \gamma_4 d10_t + \gamma_5 d11_t \\
& + \gamma_6 c15_i + \gamma_7 size_i + \varepsilon_{it}\,, \qquad i = 1, ..., 51;\, t = 1, ..., 6\,, \qquad (4.3)
\end{aligned}
$$

where IM_{it} is the net interest margin, defined as net interest income divided by a bank's total assets, of a bank i in a respective year t, LR_{it} is the LR of bank i in year t. Time dummies, $d07_t - d11_t$, are included. Results discussed in Section 3.3.1 show that banks in Switzerland possess on average the lowest LRs.[5] Thus, Swiss banks could behave statistically significantly different than all other countries, impacting regression results of Model 2. To control for this effect, a country dummy variable for Swiss banks, $c15_i$, is included in Model 2. All Swiss banks are assigned the value of one, all other countries the value of zero, as being the reference category. Again, $c15_i$ changes across panels but not across time. The variable $size_i$ is a bank specific control variable for a bank's size. This variable, defined as the natural logarithm of a bank's total assets in 2011, can exhibit a significance p-value due to the argumentation that larger banks are more likely to have a larger amount of total assets which can result in higher net interest margins. Thus this control variable is included in Model 2 to help mitigate omitted-variable biases. The variable $size_i$ is constant and unchanged in this model. Therefore, the control variable does not change over time but across panels. The intercept is β_0, and ε_{it} the unobservable random error as defined in Equation (4.2). The parameters to be estimated are β and γ. General assumptions about the error term ε_{it} are stated in Wooldridge (2010), p. 53-55 and presented in Table 4.1. Assumptions can be violated due to heteroscedasticity or autocorrelation. Regression diagnostics help to further specify the error structure of a regression model and are presented in Section 4.3. Before

i.	$E[\varepsilon_{it}] = 0$	zero mean
ii.	$E[\varepsilon_{it}^2] = \sigma^2$	constant variance
iii.	$E[\varepsilon_{it}, \varepsilon_{i,t-1}] = 0$	no autocorrelation
iv.	$E[\varepsilon_{it}, x_{it}] = 0$	no correlation with each regressor
v.	$\varepsilon_{it} \sim$	normally distributed

Table 4.1: General assumptions about the error term of a regression

parameters are attempted to be estimated, the data themselves is examined in its raw form. For the panel data regression analysis the initial sample described

[5] Germany only displays lowest LRs when the Concord Investmentbank is excluded.

in Section 3.2.1 has been extended by various financial data. The balance sheet positions total loans and receivables and the income statement positions interest income from lending transactions, total interest income, total interest expense, and net interest income have been included for the 51 banks over the period from 2006 to 2011. The additional data is retrieved from a bank's published consolidated financial statements. In order to match data from the financial risk analysis, data of four banks (Comdirect, DAB Bank, ABN Amro Holding and HBOS) is retrieved at individual bank level. Using exclusively stock-listed financial institutions ensures a high degree of comparability in accounting standards. The values at balance sheet date are representative for the respective years and used to define the four variables *loans*, *interest* and *IM* and *size*. The set of variables included in the regression models will be described in the following.

A bank's soundness is proxied by two different measures. The PD, expressed as a percentage, is employed in Model 1 as the dependent variable and represents the probability that a bank will reach its default point within a given time horizon, one year in this analysis. Figure 4.4 illustrates the development of the PD graphed by years. The PD is arithmetically derived from the DD. Thus, the variable DD is included in descriptive statistics and is expressed in numbers of standard deviations that a financial institution is away from its default point within one year. For further details and in-depth technical discussion of the construction of theses two measures see Section 3.1.2. The LR is an indicator of a bank's use of debt. This non-risk regulatory measure limits the level of debt as Tier 1 capital has to correspond to at least 3% of total assets. Discussion and calculations are presented in Section 3.1.1. Consequently, the ratio is expressed as a percentage and included in both regression models as the independent variable. The control variable *loans* of regression Model 1 is an indicator for a bank's lending activity and stands for the total amount of loans and receivables,

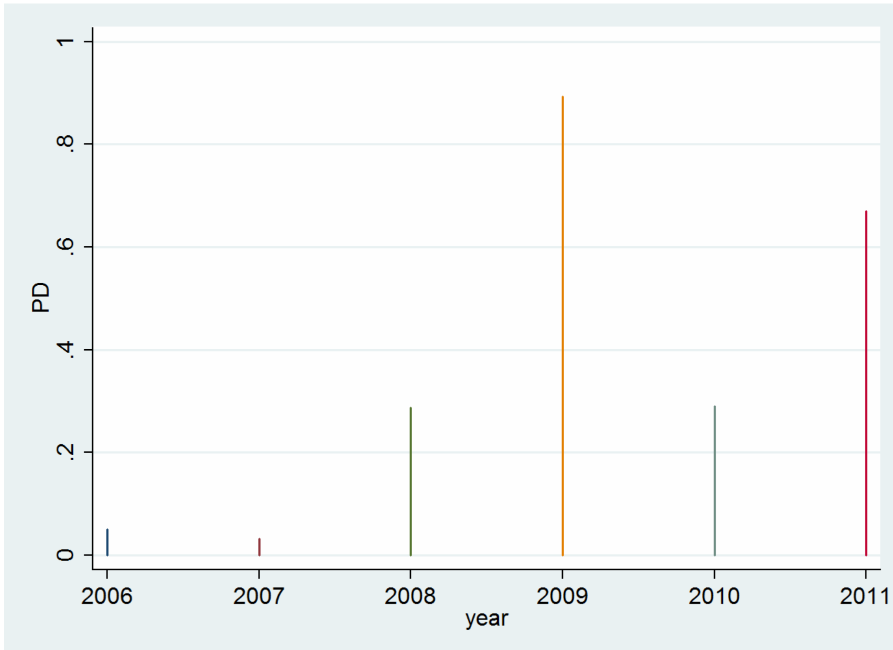

Figure 4.4: Development of the variable PD during the sample period graphed by year

expressed in billions of Euro. Baum (2006) points out that economic researchers often argue that if a percentage change in the dependent variable is related with a unit change in an independent or control variable, the relationship could be better modeled by taking the natural logarithm of the independent variable. Particularly, log transformations could help to fit the variable into the model, if the distribution of that variable has a positive skew. In order to decide whether a natural logarithm needs to be taken of the variable *loans*, a natural log is computed and both distributions are shown in a histogram Figure 4.5 which can offer valuable clues. The distribution of loans on the left side looks positively skewed. As shown on the right side of the figure, the distribution of “lnloans” still looks skewed, this time negatively. Taking the natural logarithm of the variable does not make the positively skewed distribution more normal. In contrast, the skew shifts from positively to negatively. A log transformation in this case does not help to fit the variable into the model and the regression output does not change significantly. Thus, the absolute value is taken. The variable *interest* represents

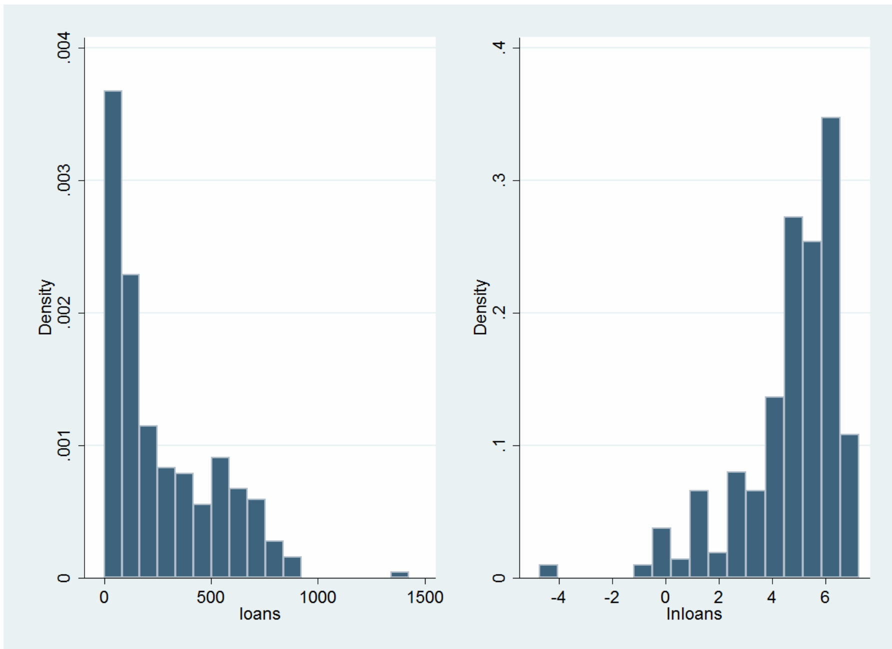

Figure 4.5: Histogram of the variable *loans* and its natural logarithm

a proxy for a bank's pricing decisions at the loan level and is defined as interest income from lending business to total loans and receivables. Accordingly, the ratio provides information on the increase or decrease of lending interest income per one unit of lending volume which results in a higher or lower cost of credit a bank charges its borrowers. Note that this variable is only monitored in order to help interpreting results regarding the net interest margin, but not included in the regression equation. This approach is selected because the dependent variable, *IM,* is biased towards the variable *interest*, i.e. the effect of *interest* is already included in the dependent variable. This effect would distort the regression. Thus, a bank's profitability in Model 2 is proxied by the net interest margin, *IM*, defined as the accounting value of a bank's net interest profit to total assets and employed as the dependent variable. The net interest margin provides information also on the contribution from maturity transformation of a bank. A positive contribution is generated due to an actively driven maturity transformation: accepting short-term deposits and making long-term loans. A higher net interest margin is due to either higher charged interest rates on loans or depressing a bank's deposit rates. The variable *interest* can give an indication of which alternative is more likely. *IM* is expressed as a percentage. The variable *size* controls the bank specific characteristic of individual size and is expressed as the natural logarithm of a bank's total assets. Time and country dummies are included to see if one year or country is behaving significantly different from the reference category. To analyze the retrieved data, the Data

Variable	Obs.	Mean	Std. Dev.	Min	Max
DD	292	4.5150	6.7916	-1.24	75.7
PD	292	0.0418	0.1108	0	0.8931
LR	301	0.0463	0.0378	0.0134	0.4848
loans	302	270.79	260.86	0.0089	1426.536
interest	247	0.0450	0.0234	0.0013	0.1813
IM	302	0.0145	0.0097	-0.0142	0.0481
size	300	5.73	1.77	1.23	8.14

Table 4.2: Descriptive Statistics Panel Data Analysis

Analysis and Statistical Software Stata 10.0 is used. After importing the sample into Stata, the data has to be converted from wide to long form. Reshaping data into the long format is necessary in order to declare the dataset to be a panel data set. The panel ID variable is set to "bank" creating 51 panels and the time variable to "year" representing 2006 to 2011. Missing values, due to inaccessible information, are replaced and stored with a missing-value code ".a". Stata automatically omits these observations from the computation. Six time dummy variables are tabulated for each year having only 2 categories, denoted by 0 and 1. Thus, coefficients are only estimated for n-1 dummy variables because all dummies are perfectly correlated and sum to one. Notes on all variable and data sources are presented in Appendix A. Descriptive statistics are reported in Table 4.2, dummies are not reported. Spearman's rank correlation coefficients are carried out using the Stata command "spearman variables, star(.01)". In this correlation method values are handled by casewise not pairwise deletion[6]. All correlation coefficients significant at the 1% level or lower are marked with three stars. Table 4.3 provides the corresponding correlation matrix. Note that

	DD	PD	LR	loans	interest	IM
DD	1.00					
PD	-0.9999***	1.00				
LR	-0.0064	0.0074	1.00			
loans	-0.2129***	0.2113***	-0.2873***	1.00		
interest	-0.0360	0.0355	0.2452***	0.0896	1.00	
IM	-0.0053	0.0060	0.7317***	-0.0704	0.5633***	1.00

Table 4.3: Correlation matrix

the LR is significantly positively correlated with the net interest margin, *IM*, whereas the correlation coefficient of the LR and the PD is not significant but also indicates a slight positive correlation, i.e. there is a trend that the LR increases as the PD increases. The correlation coefficient measures only the degree of a bivariate association. The variables are interchangeable. Any conclusions about a cause-and-effect relationship cannot be made. The purpose of correlation matrix is to investigate the relationship between variables, whereas the purpose of a regression model is to predict or explain outcomes between variables. Therefore, correlation and regression coefficients are related in the sense that both deal with relationships among variables but a significant correlation between variables does not necessarily indicate that one variable causes the other. It is only suggested that a causal relationship might exist. A correlation of zero assumes that there may not exist a causal relationship between

[6] An observation is dropped if any variable has a missing value. See Sheskin (2003) for further details on Spearman correlation.

two variables. However, a lack of correlation or significance may be due to other factors such as, poor measurements, restricted range, non-linear relationships or other extraneous factors that mask the true relationship.[7]

After presenting the empirical model and reporting descriptive statistics of panel data, regression diagnostics are performed next which explain why employing the Prais-Winsten transformation as a regression model is a consequent strategy.

4.3 Regression Diagnostics

The regression diagnostics, a set of procedures to identify influential observations and sources of collinearity, should not be neglected while analyzing panel data and are done by using Stata 10.0. First, the functional form of the relation between the variables is examined. A linear functional form is given when the dependent variable can be described as a linear function of the independent variables[8]. A scatterplot matrix is used to have a look at the relationship between all variables of Model 1 and Model 2. The dependent variable Y is demonstrated as the variable to the side of the graph while the independent variable X above or below the graph. Thus, the first row shows the scatterplots of the dependent variable against all independent variables. The scatterplot smoother "median trace" can help to identify linear trends in scatterplots and is discussed by Fox (2000). To generate the scatterplot and a scatterplot with median trace, the Stata command "graph matrix dependent_variable independent_variable(s)" and "twoway (scatter dependent_variable independent_variable(s), ms(oh)) (mband dependent_variable independent_variable(s), bands(20) clp(solid))" after "regress" are carried out. Figure 4.6 and 4.7 show that there does exist a linear trend for the majority of

[7] See Peat et al. (2009) for an in-depth discussion of correlation and regression.
[8] See Wooldridge (2010), p. 25-30, for further details on linear projection.

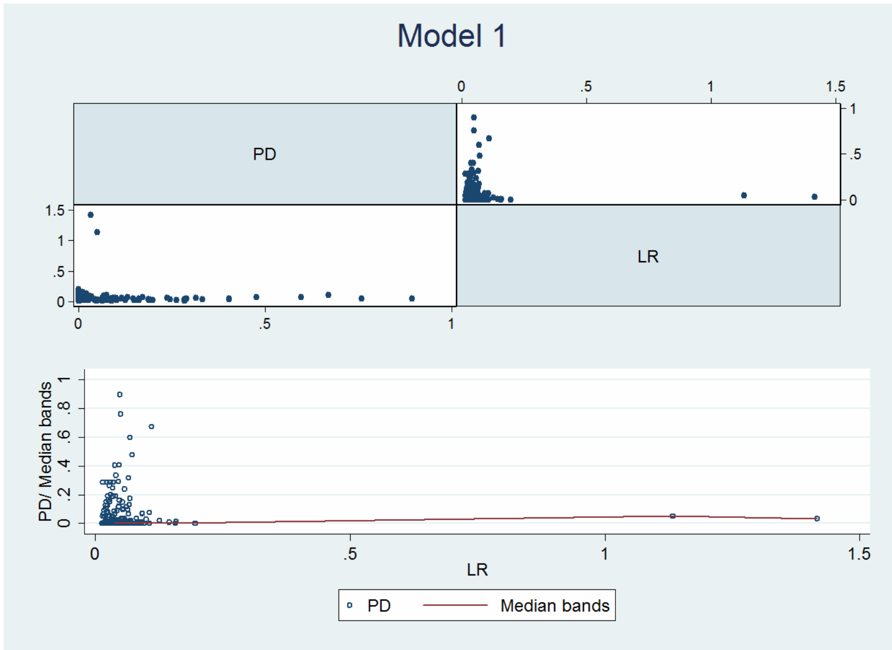

Figure 4.6: Scatterplot Model 1

This figure shows the relationship between the independent variable *LR* and the dependent variable *PD* of Model 1 in a scatterplot in order to identify linear trends.

the data, linear relations are clearly visible. In addition, it is verified whether the first assumption of the error term $E[\varepsilon_{it}] = 0$, zero mean, holds. Kohler and Kreuter (2005) argue that a violation of this assumption could result in biased regression coefficients. A residual-versus-fitted plot is carried out using Stata command "rvfplot" after "regress" to check if the mean of the residuals[9] is zero *locally*. Figure 4.8 shows that for any slice of the abscissa the mean of the residuals is zero. This holds true for Model 1 and Model 2. Thus, a violation of $E[\varepsilon_{it}] = 0$ is not obvious and further tests such as detecting signs of influential cases or omitted variables can be neglected. Linearity between the dependent

[9] A residual is defined as the difference or error between the observed observation of a dependent value or independent variable and the fitted value by the regression model. See Greene (2012), p. 66 for details on residual plots.

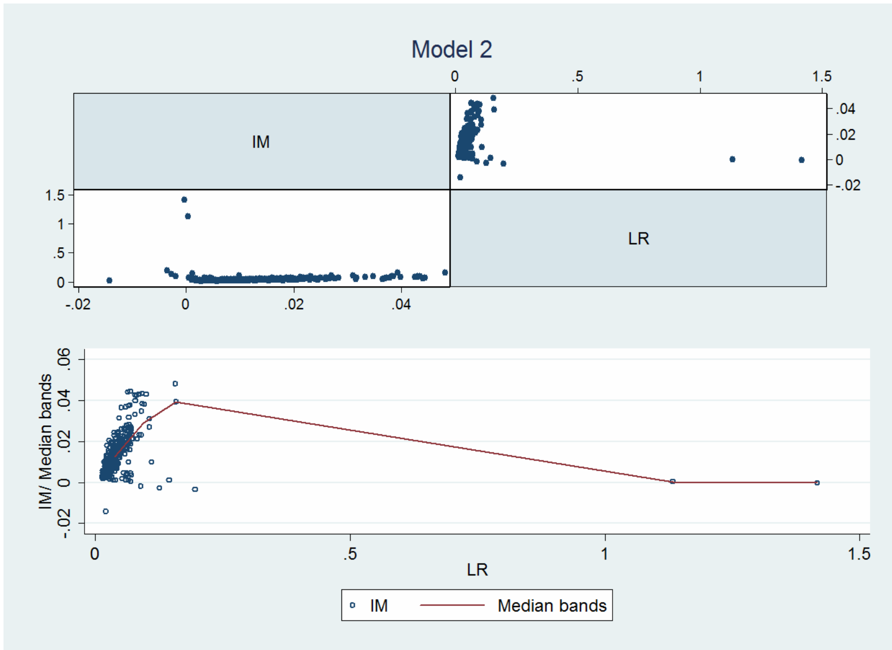

Figure 4.7: Scatterplot Model 2

This figure shows the relationship between the independent variable *LR* and the dependent variable *IM* of Model 2 in a scatterplot in order to identify linear trends.

variable and the independent variable(s) is assumed in both regression models and estimating linear regression models seems reasonable.

Second, independent variables in the multiple regression model have to be tested for multi-collinearity. Farrar and Glauber (1967) explain that multi-collinear independent variables pose a threat to the effective estimation and proper specification of the structural relationship type. A definition is given in Farrar and Glauber (1967), p. 3: “[...] an interdependency condition that can exist quite apart from the nature, or even the existence, of dependence between X and y. It is both a facet and a symptom of poor experimental design.” Baltagi (2008) argues that panel data is less plagued with multi-collinearity than,

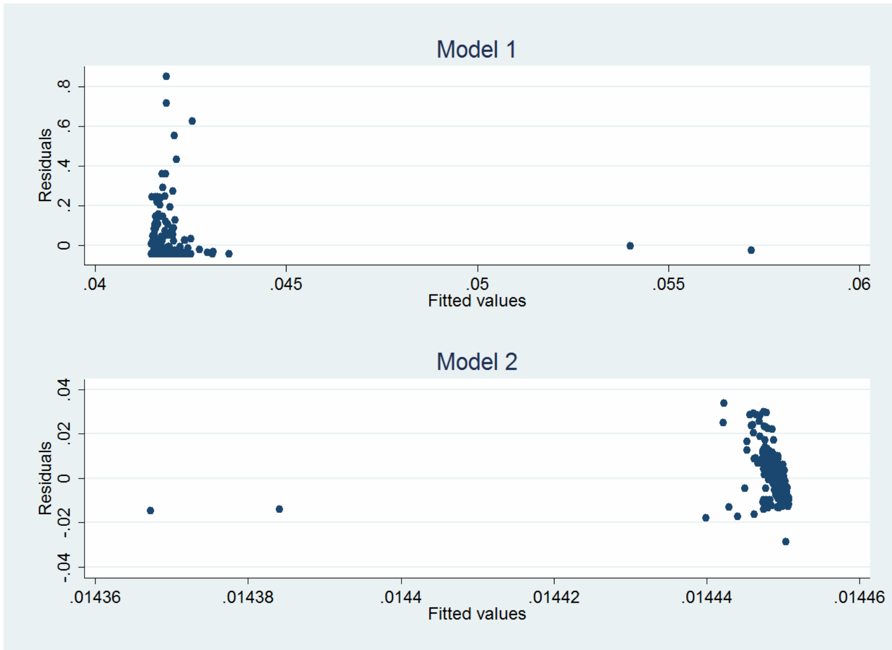

Figure 4.8: Residual-versus-fitted plots

This figure illustrates the residual-versus-fitted plots for Model 1 and Model 2 which clearly show that the mean of the residuals is zero locally.

for example, time-series data because the cross-section dimension can give more informative data and thus, adds more variability. To measure the degree of multi-collinearity, the variance inflation factor (VIF) is used. A common rule of thumb discussed in literature is that a VIF greater than 10 or a tolerance (1/VIF) less than 0.1 suggest that mutli-collinearity may be a threat[10]. To generate the VIF table the Stata command "vif" after "regress dependent_variable independent_variables" is used. Table 4.4 indicates that the VIF values do not exceed the value of 1.7. Accordingly, diagnostics are negative, i.e. there is no evidence of multi-collinearity among the independent variables. Further information on the rules of thumb regarding the VIF can be found in O'Brien

[10]See Menard (2002), Kutner et al. (2004) and Marquardt (1970).

(2007).

	Model 1		Model 2	
Variable	VIF	1/VIF	VIF	1/VIF
LR	1.0	0.98	1.1	0.9
loans	1.1	0.95		
d07	1.7	0.6	1.7	0.59
d08	1.7	0.6	1.7	0.59
d09	1.7	0.61	1.7	0.59
d10	1.7	0.6	1.7	0.58
d11	1.6	0.61	1.7	0.58
c3	1	0.99		
c15			1.1	0.95
size			1.1	0.93
Mean VIF	1.4		1.5	

Table 4.4: Variance Inflation Factor for estimating multi-collinearity

Third, error structures of both regression equations can be characterized by panel autocorrelation, i.e. the remainder disturbances are correlated and follow a first order autoregressive process AR(1). Serial correlation and its impact is discussed in Baltagi (2008). Due to an unobserved shock, such as the financial crisis in 2008, the last time period's observations can affect the behavioral relationship of current values for the next few periods. Ignoring AR(1) error structure can result in an underestimation of the standard errors, overestimation of the R^2 and too narrow confidence intervals, which lead to consistent but inefficient estimates of the regression coefficients. The Durbin-Watson statistic[11] for panel data and the Breusch-Godfrey test[12] are used to test for AR(1) autocorrelation. The former is carried out using "estat dwatson" after "regress dependent_variable independent_variable(s)" and the latter using "test" after "regress residuals on the lag". The null hypothesis that there is no autocorrela-

[11] See research done by Durbin and Watson (1950, 1951, 1971). First of all, Durbin and Watson (1950) investigated the problem of testing the error term of serial correlation. This paper is followed by Durbin and Watson (1951). Procedures for the use in practice are described. Durbin and Watson (1971) considered a number of problems arising from the test proposed earlier by the authors.

[12] See Breusch (1978).

tion of the disturbances, is rejected in each case. Statistics are listed in Table 4.5. The Durbin-Watson statistic gives evidence of positive autocorrelation in both regression models.[13] Thus, AR(1) serial correlated error component models are existent, which can be transformed into serially uncorrelated classical errors using the Prais-Winsten transformation.

	Model 1	*Model 2*
Durbin-Watson d-statistic (k, N)	(*9, 291*)	(*9, 299*)
	1.8092	0.9101
Breusch-Godfrey test	*p-value*	
	0.0000	0.0000

Table 4.5: Test for autocorrelation

The error structure of the regression models can not only suffer from autocorrelation but also from panel heteroscedasticity. This topic is covered in detail by Baltagi (2008). To make the assumption that the regression disturbance terms have the same variance across individuals and time, homoscedasticity, is very restrictive for panels, especially as the cross-sectional units, the financial institutions in the present case, are of varying size. Assuming constant variances from one panel to the next, when heteroscedastic disturbances are present, will result in consistent but not efficient estimates of the regression coefficients. Also, the standard errors will be biased. Finally, to test for heteroscedasticity the Breusch-Pagan/ Cook-Weisberg test[14] is employed using the Stata command "estat hettest" after "regress dependent_variable independent_variable(s)". The null hypothesis of constant error variance is tested and can be rejected in regression Model 1 clearly at a significance level of 5%. For regression model 2 the same result applies. The p-value is at the 0.0 level and indicates rejection of the null hypothesis. Furthermore, Greene (2003) suggest that inspecting a residual plot can help to see if the variance of the residuals change in any sys-

[13] Durbin-Watson table to determine the upper and lower critical values based on the number of observations (N) and independent variables (k) can be found in e.g. Gujarati (2003).
[14] See Breusch and Pagan (1979) or Cook and Weisberg (1983).

tematic form with the fitted (predicted) values. The residual-versus-fitted plot and a plot variation which emphasizes the variance of the residuals is shown in Figure 4.9. The Figure exhibits that the variance of the residuals slightly increases for both models. Thus, the pattern of the residuals gives convincing evidence of heteroscedastic error structure in Model 1 and Model 2, so the assumption of non-constant variance underlying this test seems to be appropriate. To verify, a second test for heteroscedasticity is employed. White (1980) test

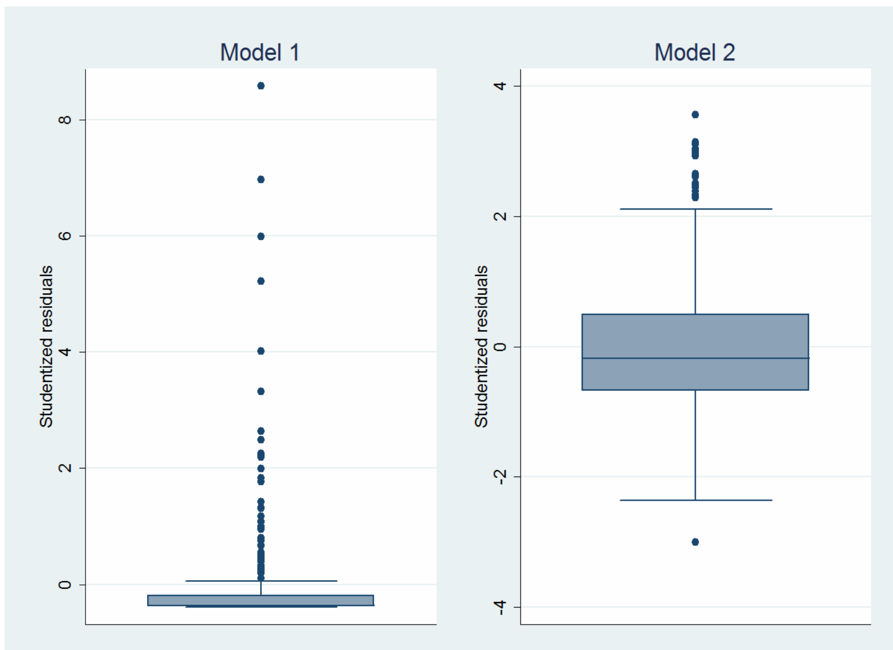

Figure 4.9: Residual plot to test for heteroscedasticity

This figure shows that the variance of the residuals increases for Model 1 and Model 2, implying heteroscedastic error structures.

is carried out using "imtest, white" after "regress dependent_variable independent_variable(s)" and tests for the null hypothesis of homoscedasticity against unrestricted heteroscedasticity. Greene (2003) argues that this test allows one to test for every form of heteroscedasticity, such as nonlinearities, by including the squares and cross products of the independent variables whereas the former test detects only linear forms. P-values clearly reject null hypothesis in each model, i.e. heteroscedastic error terms are present in both models. For p-value output see Table 4.6. For the detected presence of heteroscedastic disturbance terms, robust standard errors are computed using the Prais-Winsten transformation.

	Model 1	*Model 2*
	p-value	
Breusch-Pagan/ Cook-Weisberg test	0.0000	0.0000
White's test	0.0000	0.0000

Table 4.6: Test for heteroscedasticity

Regression diagnostics report linearity, no multi-collinearity, first-order autoregressive processes and heteroscedastic error structures. Based on these findings, the assumptions in Section 4.2 about ε_{it}, the error term, are revised and presented in Table 4.7.[15] Thus, the unobservable random error term as defined in Equation (4.2), $\varepsilon_{it} = \rho\varepsilon_{i,t-1} + u_{it}$, $\mid \rho \mid < 1$, follows a first-order autoregressive scheme over time and over individuals with an unknown autocorrelation coefficient ρ. u_{it} denotes the remainder disturbance. Performing regression di-

i.	$E[u_{it}] = 0$	the mean of disturbances is zero
ii.	$E[u_{it}^2] \neq \sigma_u^2$	the disturbances have no constant variance
iii.	$E[u_{it}, u_{i,t-1}] = 0$	disturbances are uncorrelated
iv.	$E[u_{it}, \varepsilon_{i,t-1}] = 0$	no correlation between disturbances at t and the error in the model at t-1
v.	-1 $< \rho <$ +1	rho, the autocorrelation parameter is a fraction

Table 4.7: Assumptions about the error term (revised)

agnostics detects the characteristics of the error term in the estimated regression models and justifies the Prais-Winsten transformation as a suitable regression strategy. The demarcation to other common regression models is discussed briefly in the next paragraph.

[15] For further insight see Greene (2003), p. 950-952.

The fixed-effects or random-effects regression models are commonly used techniques in existing literature for analyzing panel data and described at length in Wooldridge (2010). However, these estimation methods obtained by the ordinary least squares estimator (OLS) do not consider the underlying error structure in the regression model stated above. In addition, the fixed-effects method creates individual dummies to control any differences between the individuals. As generally accepted evidence for the whole banking sector needs to be found, controlling every individual characteristics of the banks could lead to misspecification. Parks (1967) is the first to describe a generalized least squares method (GLS), which deals with typical time-series cross section problems: autocorrelation and heteroscedasticity. Kmenta (1997) popularized the feasible generalized least squares (FGLS) estimator, which is a modification of the GLS and often used by analysts. The FGLS replaces the unknown matrix for the variance of the error term with a consistent estimator. This Parks-Kmenta method has all the options to control panel specific error structure but using it with medium- and large-scale panels is considered to be inappropriate. Beck and Katz (1995) give an explanation for this argumentation: first, this method is ruled out, if the dataset has less time dimensions T than panels N, as in this case. Second, this method tends to estimate unacceptable small standard errors. In addition, the authors give Monte Carlo evidence that panel-corrected standard errors (PCSEs) perform more accurately than usual OLS standard errors, even when complicated panel error structure is existent. It is suggested one could use GLS or FGLS coefficient estimates with PCSE to mitigate problems of the Parks-Kmenta regression method. Beck (2008) supports the choice of PCSEs. The Prais-Winsten estimator does precisely that by using an estimate of ρ. Thus, the Prais-Winsten estimator can be described as a FGLS estimator. The disturbances in the Prais-Winsten regression are, by default, heteroscedastic (each individual has its own variance) and contemporaneously correlated across panels (each pair of panels has its own covariance). Baltagi (2008) argues that cross-sectional dependence is more an issue in macro panels with time series over 20-30 years. This dataset is deemed to be a micro panel (few time periods), thus a different option is selected. It is assumed that the disturbances are only panel-level heteroscedastic with no contemporaneous correlation across panels.[16] A further option to specify is whether the pattern of the first-order autocorrelation, AR(1), is common across all panels or panel-specific. Beck and Katz (1995) argue in favor of constraining the coefficient ρ of the first-order autocorrelation process to all panels at the same point of time when testing the hypothesis of common influence. Likewise it is often assumed that things differ from case to case which indicates that one should use the panel-specific pattern of autocorrelation. The authors are aware of the trade-off between those two options. By using coefficients specific to each panel, there is a risk of bias in the estimates of the standard errors. Relying on constrained coefficients to all panels, misspecification is risked. Evidently, there does not exist theoretical justification to handle this dilemma. Therefore, for both regression equations a baseline regression model with common AR(1)[17], and a regression specification with panel-specific AR(1)[18] structure is estimated. Thus, Stata command: "xtpcse dependent_variable independent_variables, correlation (ar1) hetonly" is used for estimating the baseline regression model and "xtpcse dependent_variable independent_variables, correlation (psar1) hetonly" for the regression specification.

[16]Stata command: hetonly, see StataCorp LP (2013).

[17]Stata command: correlation (ar1)"..., within panels, there is first-order autocorrelation and that the coefficient of the AR(1) process is common to all the panels", see StataCorp LP (2013).

[18]Stata command: correlation (psar1) "..., within panels, there is first-order autocorrelation and that the coefficient of the AR(1) process is specific to each panel", see StataCorp LP (2013).

4.4 Empirical Results and Discussion

Empirical results and robustness checks of the panel data regression analysis are presented in the next section. To assess the impact of the LR on bank soundness the first hypothesis is put forward and tested in a multiple linear regression model, Model 1. To identify possible interactions between bank profitability and the LR, hypothesis two is tested in another multiple linear regression model, Model 2. Estimation results are presented for the baseline regression models and regression specifications. Missing values are replaced by a missing-value code in Stata and automatically omitted from the computation. Thus, observations with missing values in any of the variables are deleted casewise. The robustness of the findings is investigated by firstly, controlling for differences in the accounting systems in both models, secondly, omitting observations for year 2009 to 2011 in Model 1, and finally, changing the dependent variable in Model 2. As robustness test show, the regression results are not distorted significantly and can be reconfirmed.

4.4.1 Model 1

The regression analysis starts with the findings of testing the first hypothesis, the higher a bank's LR, the lower its PD. Hence, the model focuses on the impacts of imposing a limit to a bank's debt on banks' soundness in terms of the PD. Following the line of argumentation of the Basel Committee (2010a), a negative relationship between the explained and explanatory variable is expected. However, empirical results in this section confirm the opposite. Robust evidence is given that there exists a positive relationship between the regulatory and the financial soundness measure. The following estimated equation is obtained, specified exemplary for the baseline regression model

$$
\begin{aligned}
PD_{it} &= -.0201 + .0495 LR_{it} - .002 d07_t + .0536 d08_t + .1424 d09_t \\
&\quad + .0091 d10_t + .0321 d11_t + .2507 c3_i + 4.0e^{-05} loans_{it}\,. \qquad (4.4)
\end{aligned}
$$

Further estimation results and goodness-of-fit measures are reported in Table 4.8. The PD is the dependent variable and the explanatory variable is the LR. Estimation results are also presented for dummies. The baseline regression model (1) with common AR(1) error structure and the regression specification (2) with panel-specific AR(1) error structure include 291 observations and 51 panels. The reference category, year 2006, is excluded. The heteroscedastic corrected standard errors are reported in parenthesis. The constant term is included in the model, as Equation (4.4) demonstrates, but not reported in Table 4.8. Statistical significance is marked as follows: ***, **, * for 1, 5 and 10% level. The goodness-of-fit measures R^2 and Wald statistics are computed for the entire system of equations whereas the standard errors are reported for each equation individually. The fit seems adequate. Overall, panel specific correction improves the results, see results of the regression specification (2).

The pattern of the coefficients on year dummies, *d07-d11,* is itself of interest and can be interpreted as follows: the coefficient on *d07*, e.g. implies that, holding all other factors fixed, a bank had on average a “0.2%” lower PD than in the reference year 2006. In the following years, a bank’s PD is on average higher than in 2006. Note that the time dummies, *d08, d09* and *d11,* exhibit a significantly positive effect on the regression (1) and (2) at the 10% level and lower. The value of the PD of a bank in 2009 is on average 14% higher than the PD in the reference period 2006. The regression model reflects the financial crisis with its beginning in 2008 and confirms results of the financial risk analysis presented in Section 3.3. The coefficient on the country dummy, *c3*, exhibits

	(1) PD	(2) PD
Independent variables		
LR	.0495***	.0532***
	(.0155)	(.0081)
Dummy/ control variables		
d07	-.002	.0003
	(.0155)	(.0147)
d08	.0536***	.0557***
	(.017)	(.016)
d09	.1424***	.1405***
	(.0171)	(.0162)
d10	.0091	.0093
	(.0172)	(.0164)
d11	.0321*	.0312*
	(.0169)	(.0167)
c3	.2507***	.2488***
	(.087)	(.0761)
loans	4e-05**	5.7e-05***
	(1.8e-05)	(1.9e-05)
Measure of fit		
R^2	0.3855	0.4437
Wald chi2(6)	113.99	139.07
Prob > chi2	0.0000	0.0000
No. of obs.	291	291

Table 4.8: Estimation results of Model 1

The panel model estimated is $PD_{it} = \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 d09_t + \gamma_4 d10_t + \gamma_5 d11_t + \gamma_6 c3_i + \gamma_7 loans_{it} + \varepsilon_{it}$. Baseline regression model (1) controls common AR(1). Specification (2) controls panel-specific AR(1). Constant term is included but not reported. Panel-corrected standard errors are reported in parenthesis. ***, **, *: statistically significant at the 1, 5, and 10% level.

a significantly positive effect on the regression at the 1% level in the baseline regression (1) and in the regression specification (2). The banks in Ireland had on average a "25%" higher PD than the reference category which is defined as of the other countries. Thus, it is necessary to control for the country of Ireland. Further information is discussed before, in Sections 3.3.2 and 4.2. The coefficient on the control variable *loans* exhibits a significantly positive sign at the 5% level in the baseline regression (1) and at the 1% level in the regression specification (2). The assumption is valid that this control variable is associated with the dependent variable but the inclusion does not change estimates of the explanatory variable *LR* as stated next. The *LR* variable enters the baseline regression model (1) significantly positive at the 1% level, indicating that the higher the LR, the higher the PD of each financial institution. More precisely, a one-percent change in the *LR* generates a "0.05%" change in the variable *PD*. The regression specification model (2) yields identical results and confirms statistical significance. Exact data of the Stata output is presented in Appendix B.1.

It is concluded that the sign of the coefficient is inconsistent with prediction theories provided by the BCBS. Thus, the first research hypothesis put forward is rejected. The findings do not confirm theoretical models by supervisors predicting a positive effect of a leverage constraint on a bank's soundness. Results show that a bank's probability of default is positively related to it's leverage ratio. Therefore, banks with a higher LR possessed a higher default probability in the sample implicating that these banks are more vulnerable and less stable.

If imposing a limit to a bank's debt does not promote greater resilience of each individual financial institution, least of all, stability of the whole banking system will be improved. To sum up, banks with a high LR are regarded as sound and stable by supervisors. However, this empirical analysis suggests that there is a positive relationship between the LR and the PD, i.e. banks with a high LR are more fragile and vulnerable than banks that possess low LRs. Empirical findings on this effect are in line with the argumentation of academic researchers who are concerned about the new regulatory measure, see Section 2.3.

Next, results of Model 2 are provided to detect reasons for the significantly positive relationship between the regulatory and the financial soundness measure.

4.4.2 Model 2

Empirical results suggest that the higher a bank's LR, the higher its PD. Results are contradictory to the intentions of supervisors who belief that a binding constraint on levels of leverage contributes to enhancing financial stability as a whole. A second regression analysis is employed to detect potential reasons for the rejection of H1 by testing the suggested research hypotheses H2: a bank's LR is positively related to its profitability. Thus, Model 2 focuses on the nexus between the regulatory constraint of a bank's debt and its lending business activity from the perspective of profitability.

The following estimated equation is obtained for the baseline regression model

$$\begin{aligned} IM_{it} &= +.0075 + .1333LR_{it} - .0003d07_t + .0018d08_t + .0012d09_t \\ &\quad -.0002d10_t - .0006d11_t - .0071c15_i + .0002size_i\,. \end{aligned} \tag{4.5}$$

Estimation results for the baseline regression model (1) controlling common AR(1) and the regression specification (2) controlling panel-specific AR(1) plus goodness-of fit measures are presented in Table 4.9. Stata output can be found in Appendix B.2. Numbers and stars can be interpreted the same way as in

Table 4.8. The net interest margin, *IM*, is the explained variable, whereas the *LR* is the explanatory variable. In addition, the bank specific control variable *size* is included. Time and country dummies are included, year 2006 as the reference category is again excluded. Model 2 includes 299 observations and 50 panels due to unavailability of data of the Concord Investmentbank. Wald statistics indicate that the model has an adequate fit and the results are slightly improved by controlling panel specific AR(1). The coefficients are calculated by controlling the effect of all other explanatory variables in a multiple regression model. It is ensured that when analyzing the effect of changing one independent variable by one unit, all other variables are held constant.

Time dummies are not informative and meaningful in this second regression model. Again, the coefficients can be interpreted as follows: the coefficient on *d09*, for example, implies that, holding all other factors fixed, the value of the net interest margin in 2009 differs "0.12%" from the *IM* in the reference category 2006. However, no coefficient displays a statistically significant sign, i.e. the banks net interest margin does not behave significantly differently than in the reference category 2006. Coefficient of the country dummy *c15*, Switzerland, exhibits a significantly negative sign at the 1% level for the baseline regression (1) and the regressions specification (2). Results indicate that the two banks of Switzerland which display on average the lowest LRs in the sample, possess on average a "0.71%" lower net interest margin compared to the reference category, 'all other countries'. See Sections 3.3.1 and 4.2 for further information. The control variable *size* does not enter the regressions significantly. Thus, this control variable is not associated with the dependent variable. The explanatory variable, *LR*, enters both regression equations (1) significantly positive at the 5% level and (2) at the 10% level, suggesting a positive relationship between a bank's profitability and its LR, i.e. banks with higher LRs had on average

	(1) IM	(2) IM
Independent variables		
LR	.1333**	.1026*
	(.0616)	(.0582)
Dummy/ control variables		
d07	-.0003	-.0001
	(.001)	(.0008)
d08	.0018	.0016
	(.0012)	(.001)
d09	.0012	.0008
	(.0013)	(.0011)
d10	-.0002	-.0006
	(.0014)	(.0012)
d11	-.0006	-.0009
	(.0015)	(.0013)
c15	-.0071***	-.007***
	(.0013)	(.0011)
size	.0002	.0002
	(.0005)	(.0004)
Measure of fit		
R^2	0.2036	0.5879
Wald chi2(8)	125.98	164.48
Prob > chi2	0.0000	0.0000
No. of obs.	299	299

Table 4.9: Estimation results of Model 2

The panel model estimated is $IM_{it} = \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 d09_t + \gamma_4 d10_t + \gamma_5 d11_t + \gamma_6 c15_i + \gamma_7 size_i + \varepsilon_{it}$. Baseline regression model (1) controls common AR(1). Specification (2) controls panel-specific AR(1). Constant term is included but not reported. Panel-corrected standard errors are reported in parenthesis. ***, **, *: statistically significant at the 1, 5, and 10% level.

higher net interest margins. More precisely, a one-percent change in the *LR* generates a "0.13%" change in the variable *IM*. Hypothesis H2 can be accepted, suggesting that a bank's net interest margin is positively related to its leverage ratio. A positive contribution is generated due to either higher charged interest rates on loans or depressing a bank's deposit rates. The monitored variable *interest* represents a ratio of interest income to total loans. The strong significant positive correlation, see Table 4.3, between this variable with the variables *LR* and *IM*, can give an indication that banks generate higher net interest margins by raising their interest rates on loans. This argumentation is in line with research done by Demirgüç-Kunt and Huizinga (1999), see Section 4.1, giving evidence of a positive relationship between interest rates and the interest margin. Whether banks raise their interest rates because they have to generate profit from less lending, due to steadily increasing capital requirements, or both is not resolved definitively, see Section 4.1. Nevertheless, the strong correlation between the variable *LR* and *loans* indicates that banks with a high LR had on average lower lending activity, see Table 4.3. It can be assumed, that the LR requirement will affect loan supply, i.e. a bank tries to generate higher LRs in the future by limiting the number of loans. In this context, banks would offer credit at a price at which demand is expected to exceed supply. The latter would confirm previous theoretical and empirical models predicting that higher costs associated with raising the required capital are passed on to a bank's borrowers, see Section 2.3. In this case, the Modigliani and Miller (1958) theorem, that a corporation's decision is not influenced by the source of financing, is not validated. Consequently, hints of a banks' level of equity influencing its loan pricing decision can be taken as a violation of this theorem.

Next, the thesis will discuss possible implications of the interpreted regression results on financial stability following Stiglitz and Weiss (1981) framework.

In contrast to intentions of supervisors, regression results of Model 1 validate that a higher LR does not enhance a bank's soundness but increases the PD of each financial institution. Banks with a low LR had on average a lower PD than banks with a high LR in the sample during the tested observation period. Findings of the regression Model 2 confirm this empirical evidence by identifying possible triggers of the positive relationship between the LR and PD. Empirical evidence is given that a LR requirement can lead to a higher net interest margin which presumably results from higher charged loan interest rates. Findings demonstrate that banks with high LRs had on average higher net interest margins during the sample period. This observable effect can have major impacts on the stability of the financial system as a whole which are discussed by Stiglitz and Weiss (1981). In this context, their framework can be seen as an explanatory approach why the acceptance of H2 leads to the rejection of H1. Detailed explanation is given in Section 4.1 and presented graphically in Figure 4.3. The discussed impacts of higher loan interest rates on the "riskiness" of a bank by Stiglitz and Weiss (1981) are conceivable and result in less stability at individual bank level and a vulnerable banking system. Overall, regression results show that the LR requirement, as proposed by the BCBS, does not help to maintain financial stability but has a number of side-effects. The bottom line is that these side-effects give banks the incentive to cut back on lending and to raise their net interest margins by increasing loan interest rates. Due to the adverse selection and incentive effect discussed byStiglitz and Weiss (1981), low risk investors drop out of the market. Dramatic risk-shifting from low-risk to high-risk loan portfolios is expected. This concentration of risk in the micro-prudential dimension increases the vulnerability of the banking system at the macro-level.

The next section investigates the robustness of the empirical findings.

4.5 Robustness Check

Several robustness tests for the prior regression results are provided in this section, in order to ensure their validity. Three different robustness checks are employed: the robustness check specification (1) controls for differences in accounting regimes by including the dummy variable *IFRS* in both models, Model 1 and Model 2. Specification (2) is estimated for Model 1 by reducing the observation period excluding observations for 2009-2011. Specification (3) is estimated by modifying the dependent variable for Model 2. Estimated results of the robustness check are presented in Table 4.10 for Model 1 and in Table 4.11 for Model 2. Findings demonstrate that initial results are robust. The exact data of stata output is given in Appendix C. Levels of significance are unmodified at the 1, 5 and 10% level and starred with ***, **, * respectively. The pattern of the first-order autocorrelation is specified as common across all panels, common AR(1), for all robustness checks. It is desists from using panel-specific AR(1), because regression results did not change significantly, rather were slightly improved. To begin with, robustness is evaluated by including a further dummy variable into the regression equations (specification (1)), to control for different accounting standards. Model 1 is estimated as following

$$\begin{aligned} PD_{it} &= \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 d09_t + \gamma_4 d10_t \\ &\quad + \gamma_5 d11_t + \gamma_6 c3_i + \gamma_7 loans_{it} + \gamma_8 IFRS_i + \varepsilon_{it}\,, \end{aligned} \tag{4.6}$$

and Model 2

$$\begin{aligned} IM_{it} &= \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 d09_t + \gamma_4 d10_t \\ &\quad + \gamma_5 d11_t + \gamma_6 c15_i + \gamma_7 size_i + \gamma_8 IFRS_i + \varepsilon_{it}\,. \end{aligned} \tag{4.7}$$

European banks' financial statements are reported under IFRS whereas banks outside Europe are not necessarily required to adopt IFRS. The sample includes banks of the United States of America which report under US GAAP. Different key accounting standards could have material impact on reported financial results as shown in Section 3.3.1. To investigate, whether different accounting systems significantly affect regression results, the dummy variable *IFRS* is included and represents all banks which report under IFRS. Hence, US banks reporting under US GAAP represent the reference category. The dummy does not change across time but across panels and has no significant coefficient in Model 1 and Model 2, and thus can be excluded. It is ruled out that results are driven by accounting-specific factors. Accordingly, reported results of this robustness check show that main findings are reconfirmed even when controlling differences in accounting standards. To sum up, hypothesis H1 is still rejected and H2 accepted.

Further robustness is checked by changing the observation period. All sample observations for the years 2009, 2010 and 2011 are removed. In Model 1 year 2009 and 2011, behave significantly different than the rest. In addition, the previous financial risk analysis in Section 3.3.2 suggests that the financial crisis had its worst impact on financial institutions in 2009 and that year 2011 may be impacted by the European sovereign debt crisis. Thus, robustness check specification (2) only includes observations for 2006 until 2008. The equation of Model 1 is

$$PD_{it} = \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 c3_i + \gamma_4 loans_{it} + \varepsilon_{it}\,. \qquad (4.8)$$

Note that this robustness check is performed solely for Model 1. Main findings of Model 2 demonstrate that the regression is not driven by time specific effects (the coefficients on time dummies do not exhibit a significant sign, see Table

4.9). It is concluded that significance of the variables remains robust in Model 1, reflecting that results are validated and not driven by the aftermath of the financial crisis. During this observation period, coefficient of the country dummy do exhibit a significant sign at the 10% level, indicating that the country Ireland did behave statistically differently during the years from 2006 to 2008, as well. To conclude, rejection of hypothesis H1 is reconfirmed.

Finally, another robustness check is provided for Model 2. The regression equation is modified, specification (3), by using a comparable dependent variable, *interestinc*, changing the model to

$$\begin{aligned} interestinc_{it} &= \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 d09_t + \gamma_4 d10_t \\ &\quad + \gamma_5 d11_t + \gamma_6 c15_i + \gamma_7 size_i + \varepsilon_{it}\,, \end{aligned} \tag{4.9}$$

where the variable *interestinc* is another proxy for bank's profitability, defined as the interest income a bank earned from lending business divided by total assets. This variable changes across panels and time. Thus, the dependent variable *IM* is modified slightly by changing the numerator of this variable. *Interestinc* considers only the interest a bank charged its borrowers per total assets but not the interest expense. The coefficient on the variable *LR* exhibits a significantly positive sign at the 5% level. Banks with a high LR had on average a "0.15" higher interest income per total assets, i.e. banks with a higher LR were more profitable than banks with a lower LR. Employing this comparable dependent variable helps to further determine how banks are generating higher net interest margins as a reaction to the LR requirement. Findings of this robustness check give strong statistical evidence that banks generate higher net interest margins by raising their interest rates on loans than depressing deposit rates. Note that robustness check specification (3) is driven by time specific effects but these effects do not change the estimates of the explanatory variable significantly. In this respect, the main regression results are valid and H2 still is accepted.

The general performance of all robustness check regression specifications indicate a good model fit. None of the alternative settings changes the main regression coefficient estimates significantly. The research hypothesis H1 is rejected. The variable LR enters each regression significantly positive at the 1% level. As shown, the two estimated robustness check specifications for Model 1 indicate a statistical significant positive relationship between a bank's LR and its PD, indicating that a LR requirement does not enhance banks soundness but has the opposite effect. In addition, robustness checks for Model 2 show that H2 still can be supported. Thus, the results of Model 2 are reconfirmed, suggesting that a bank's profitability depends positively on a bank's LR. To sum up, the coefficients are plausible and robust, evidence of structural validity is given.

	(1) PD	(2) PD
Independent variables		
LR	.0474***	.0375***
	(.0154)	(.0075)
Dummy/ control variables		
d07	-.0023	-.002
	(.0153)	(.0085)
d08	.0533***	.0539***
	(.0169)	(.0076)
d09	.1421***	
	(.0171)	
d10	.0088	
	(.0172)	
d11	.0341**	
	(.017)	
c3	.2525***	.0265*
	(.0895)	(.0138)
loans	3.28e-05*	3.58e-05**
	(1.68e-05)	(1.62e-05)
IFRS	-.0422	
	(.0327)	
Measure of fit		
R^2	0.3875	0.3622
Wald chi2(6)	115.73	80.63
Prob > chi2	0.0000	0.0000
No. of obs.	291	150

Table 4.10: Results of robustness checks Model 1

The panel model estimated is $PD_{it} = \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 d09_t + \gamma_4 d10_t + \gamma_5 d11_t + \gamma_6 c3_i + \gamma_7 loans_{it} + \gamma_8 IFRS_i + \varepsilon_{it}$ for robustness check specification (1), and $PD_{it} = \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 c3_i + \gamma_4 loans_{it} + \varepsilon_{it}$ for robustness check specification (2). Constant term is included but not reported. Panel-corrected standard errors are reported in parenthesis. ***, **, *: statistically significant at the 1, 5, and 10% level.

	(1) IM	(3) interestinc
Independent variables		
LR	.1298** (.0632)	.1459** (.068)
Dummy/ control variables		
d07	-.0003 (.001)	.0042*** (.0015)
d08	.0018 (.0012)	.0083*** (.0019)
d09	.0012 (.0013)	-.0026 (.0022)
d10	-.0002 (.0014)	-.0058** (.0023)
d11	-.0006 (.0014)	-.0049** (.0025)
c15	-.0067*** (.0012)	-.0158*** (.0031)
size	2.36e-05 (.0005)	.0004 (.0007)
IFRS	-.0032 (.0031)	
Measure of fit		
R^2	0.208	0.3656
Wald chi2(8)	130.75	104.69
Prob > chi2	0.0000	0.0000
No. of obs.	299	246

Table 4.11: Results of robustness checks Model 2

The panel model estimated is $IM_{it} = \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 d09_t + \gamma_4 d10_t + \gamma_5 d11_t + \gamma_6 c15_i + \gamma_7 size_i + \gamma_8 IFRS_i + \varepsilon_{it}$ for robustness check specification (1), and $interestinc_{it} = \beta_0 + \beta_1 LR_{it} + \gamma_1 d07_t + \gamma_2 d08_t + \gamma_3 d09_t + \gamma_4 d10_t + \gamma_5 d11_t + \gamma_6 c15_i + \gamma_7 size_i + \varepsilon_{it}$ for robustness check specification (2). Constant term is included but not reported. Panel-corrected standard errors are reported in parenthesis. ***, **, *: statistically significant at the 1, 5, and 10% level.

Chapter 5

Conclusion and Outlook

Research questions which address the constantly evolving regulation of financial institutions are covered in this thesis. More precisely, the new non-risk based LR proposed by the BCBS and its relevance to the regulated institutions and to the stability of the global financial system is analyzed. Existing literature in this area is picked up and carried further by finding empirical evidence for recently emerging assumptions by academic researchers on possible side effects of the LR. Findings of this thesis demonstrate that a LR requirement has the unintended consequence of increasing risk in the financial system rather than reducing it. Chapter 3 starts with the theoretical description of the LR, as an indicator of a bank's use of debt, and the financial soundness measures DD and PD. It is argued that the DD and PD are an effective measure for determining the default probability of financial institutions because this model employs both financial statements and market prices. The Black and Scholes (1973) and Merton (1974) model is applied as a theoretical framework. It is a well-known option pricing model among academic researchers and practitioners. After clarifying the theoretical underpinnings, a financial risk analysis is employed to investigate the capitalization and soundness of the banking sector. The regulatory constraint and the financial soundness measures are computed for a sample of 51 stock-listed banks headquartered in Europe and the US over the period from 2006 to 2011. Findings regarding the LR are in line with the Basel III Monitoring exercise by the EBA, BCBS and German Central Bank. Overall, it can be concluded that the LR is slightly higher in the years after the financial crisis and that banks averagely meet the calibration target of 3% during the sample period even though capital capitalization varies considerably across countries. Swiss banks display the lowest LR of all banks and struggle to meet the 3% Tier 1 LR level. In contrast, US banks possess very high LR of about 6.3% As discussed by Morris and Shin (2008), and empirical findings in Chapter 4 show, one reason could be the difference in accounting regimes. Findings regarding the PD series demonstrate that banks have very low PDs in 2006 and 2007. The banking system is considered to be sound and healthy. The PD increases sharply in 2008 and reaches its peak in 2009. The global financial crisis has affected the banking sector by putting banks under financial distress. Financial stability is jeopardized dramatically. After 2009, bank soundness and the overall stability of the financial system recovers according to the PD series, even though, the European sovereign debt crisis seems to impact banks in late 2011. In conclusion, banks display higher LRs and PDs during the years of the global financial crisis 2008 and 2009.

In Chapter 4, a panel data regression is employed to analyze, first of all, the nexus between the LR and the PD. Statistical evidence is given that there is a positive relationship between these two measures, implying that the higher the LR of a bank the higher its PD. It can be concluded that imposing a limit to a bank's debt does not promote greater resilience on individual financial institution and results in destabilizing the global financial system. The theory by Stiglitz and Weiss (1981) is considered as an explanation for this effect. Further, empirical findings are in line with the argumentation of, for example, Kamada and Nasu (2010) and Hakura and Cosimano (2011) who view the new regulatory measure with disquiet. Reasons for a positive relationship between the LR and PD are detected by employing a second panel data regression model. Further statistical evidence is provided that a bank's LR is positively related to its profitability. It is concluded that banks definitely generate higher net interest margins by raising their interest rates on loans. Furthermore, two possibilities of how a bank increases its net interest margin are conceivable: due to a cut back on lending (the bank needs to generate profit from lower lending), and/or passing on the operating cost of increasing regulatory capital on to borrowers. The former confirms research done by Kashyap et al. (2010) that banks prefer to reduce total assets by cutting back on lending than increasing Tier 1 capital in order to meet the calibration target. Cutting back on lending triggers major negative effects for the overall economy. The latter, is in line with evidence given by Demirgüç-Kunt and Huizinga (1999) that higher cost, associated with raising required regulatory capital, are passed on to a bank's borrowers. This implies that the theory provided by Stiglitz and Weiss (1981) can be seen as an explanation why the LR requirement leads to higher probabilities of default: higher charged interest rates by a bank affect the riskiness of a loan due to the adverse selection and incentive effect. This concentration of risk in the microprudential dimension strongly destabilizes the global financial system as discussed by Stiglitz and Weiss (1981). To conclude, regression results show that the LR requirement does not help to maintain financial stability at individual bank level due to a number of side-effects. These side-effects result in a more vulnerable and fragile banking sector which is hallmarked by financial distress.

Still, there is a large number of research questions left for future research. First of all, regulatory interactions are not considered in this thesis. As the LR constraint is proposed just as one part of an extensive regulatory framework, it might be worthwhile to consider the interaction between the different regulatory requirements for future research. No single measure would have prevented the global financial crisis, and an adequate regulatory framework requires a menu of macro- and microprudential tools. It is questionable whether results will differ when the measures are considered in conjunction with one another. Furthermore, an in-depth analysis of macroeconomic effects of the risk-weighted measures and the LR is necessary in order to predict implications not only for the banking system, but for the public sector. In addition, it is up for discussion whether the implementation of Basel III into European law gives financial institutions in the Euro-zone the incentive to stock up on high risk sovereign debt which does not require a higher capital charge. Finally, considering the interconnectedness of financial institutions could be worthwhile, if the factor "too interconnected" plays a role in evolving regulatory frameworks. The resulting exposure of interconnected, systemically important institutions revealed on balance sheets could have an impact on the LR. To sum up, the high practical relevance of research in the area of financial regulation continues as banking crisis have been more frequent than anticipated and regulation seems to lag behind.

Chapter 6

List of Symbols

The relevant symbols are stated and sorted in order of appearance.

6.1 Symbols Chapter 2

$r*$	"Bank optimal" rate
C	Random amount
r_S^*	Max. interest rate (low risk borrower)
r_R^*	Max. interest rate (high risk borrower)
μ	Min. return
$f_S(\cdot)$	Density function (low risk borrower)
$f_R(\cdot)$	Density function (high risk borrower)
$F_S(\cdot)$	Cum. distribution function (low risk borrower)
$F_R(\cdot)$	Cum. distribution function (high risk borrower)

6.2 Symbols Chapter 3

LR	Leverage ratio
E	Equity
V_A	Value of assets
D	Default point
T	Time horizon
t	Time
i	Panel ID
dV_A	Change in asset value
μ	Drift
μ_E	Expected return on equity
σ_A	Asset volatility
W	Standard Wiener process
V_E	Value of equity
σ_E	Equity volatility
r	Risk-free rate
$N(\cdot)$	Cum. stand. normal distribution
L_s	Short-term liabilities
L_l	Long-term liabilities
ε	Random component
d	Distance from D
DD	Distance to default
PD	Probability of default
R	Simple interest rate

6.3 Symbols Chapter 4

y	Dependent variable
β_0	Intercept
β, γ	Parameters to be estimated
ε	Random error
ρ	Autocorrelation coefficient
μ	Remainder disturbance
R^2	Measure of fit
b	Standardized regression coefficient

Appendix

Appendix A

Appendix Section 4.2

Variable	Description	Data Sources
DD	First proxy for the soundness of bank i in a respective year t	Financial statements, Datastream, own calculations
PD	Second proxy for banks' soundness of bank i in a respective year t	Financial statements, Datastream, own calculations
LR	Indicator for a bank's use of debt	Financial statements, own calculations
loans	Indicator for a bank's lending activity: total amount of loans and receivables	Financial statements
interest	Proxy for a bank's interest income: income from lending business/ loans	Financial statements, own calculations
IM	Proxy for a bank's profitability: net interest income/ total assets	Financial statements, own calculations
size	Proxy for a bank's size: ln(total assets)	Financial statements, own calculations
c3, c15	Country dummies representing: c3 Ireland and c15 Switzerland	
d07	Time dummy variable year 2007	
d08	Time dummy variable year 2008	
d09	Time dummy variable year 2009	
d10	Time dummy variable year 2010	
d11	Time dummy variable year 2011	

Table A.1: Notes on variables and data sources

Appendix B

Appendix Section 4.4

B.1 Stata Regression Output Model 1

```
. xtpcse PD LR d07-d11 c3 loans, c(a) het
(note: estimates of rho outside [-1,1] bounded to be in the range [-1,1])

Prais-Winsten regression, heteroskedastic panels corrected standard errors

Group variable:   bank                          Number of obs      =       291
Time variable:    year                          Number of groups   =        51
Panels:           heteroskedastic (unbalanced)  Obs per group: min =         2
Autocorrelation:  common AR(1)                                 avg =  5.705882
                                                               max =         6
Estimated covariances      =        51          R-squared          =    0.3855
Estimated autocorrelations =         1          Wald chi2(8)       =    113.99
Estimated coefficients     =         9          Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |           Het-corrected
          PD |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          LR |   .0495125   .0154694     3.20   0.001      .019193     .079832
         d07 |  -.0020115   .0155348    -0.13   0.897    -.0324592    .0284363
         d08 |   .0536256   .0169638     3.16   0.002     .0203772     .086874
         d09 |   .1424083   .0171304     8.31   0.000     .1088334    .1759831
         d10 |    .009095   .0171801     0.53   0.597    -.0245774    .0427674
         d11 |   .0321307   .0169282     1.90   0.058    -.0010481    .0653094
          c3 |   .2506802   .0870051     2.88   0.004     .0801533    .4212071
       loans |     .00004   .0000178     2.25   0.024     5.20e-06    .0000748
       _cons |  -.0200766   .0113539    -1.77   0.077    -.0423299    .0021767
-------------+----------------------------------------------------------------
         rho |   .1268412
------------------------------------------------------------------------------
```

Figure B.1: Stata regression output Model 1 controlling common AR(1)

```
. xtpcse PD LR d07-d11 c3 loans, c(p) het
(note: estimates of rho outside [-1,1] bounded to be in the range [-1,1])

Prais-Winsten regression, heteroskedastic panels corrected standard errors

Group variable:   bank                            Number of obs      =       291
Time variable:    year                            Number of groups   =        51
Panels:           heteroskedastic (unbalanced)    Obs per group: min =         2
Autocorrelation:  panel-specific AR(1)                           avg =  5.705882
                                                                 max =         6
Estimated covariances      =        51            R-squared          =    0.4437
Estimated autocorrelations =        51            Wald chi2(8)       =    139.07
Estimated coefficients     =         9            Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |           Het-corrected
          PD |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          LR |   .0531876   .0080862     6.58   0.000     .0373389    .0690362
         d07 |   .0003472    .014728     0.02   0.981     -.028519    .0292135
         d08 |   .0557237    .016049     3.47   0.001     .0242683    .0871791
         d09 |   .1404734   .0162364     8.65   0.000     .1086507    .1722961
         d10 |   .0092628   .0164126     0.56   0.573    -.0229053    .0414309
         d11 |   .0312288   .0167147     1.87   0.062    -.0015314     .063989
          c3 |   .2488105   .0761415     3.27   0.001     .0995759    .3980452
       loans |   .0000569   .0000193     2.95   0.003     .0000192    .0000947
       _cons |  -.0238053   .0111267    -2.14   0.032    -.0456131   -.0019974
-------------+----------------------------------------------------------------
        rhos =  .2969041  .0887984  .4243597 -.9501771  .0323769 ... -.3769286
------------------------------------------------------------------------------
```

Figure B.2: Stata regression output Model 1 controlling panel-specific AR(1)

B.2 Stata Regression Output Model 2

```
. xtpcse IM LR d07-d11 c15 size, c(a) het
(note: estimates of rho outside [-1,1] bounded to be in the range [-1,1])

Prais-Winsten regression, heteroskedastic panels corrected standard errors

Group variable:   bank                          Number of obs      =       299
Time variable:    year                          Number of groups   =        50
Panels:           heteroskedastic (unbalanced)  Obs per group: min =         5
Autocorrelation:  common AR(1)                                 avg =      5.98
                                                               max =         6
Estimated covariances      =        50          R-squared          =    0.2036
Estimated autocorrelations =         1          Wald chi2(8)       =    125.98
Estimated coefficients     =         9          Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |           Het-corrected
          IM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          LR |   .1332602   .0615791     2.16   0.030     .0125674    .2539531
         d07 |  -.0003027   .0009713    -0.31   0.755    -.0022064    .0016011
         d08 |    .001819   .0012199     1.49   0.136    -.0005719      .00421
         d09 |   .0012434   .0013041     0.95   0.340    -.0013127    .0037994
         d10 |  -.0001825   .0013941    -0.13   0.896    -.0029149    .0025498
         d11 |  -.0006018   .0014728    -0.41   0.683    -.0034884    .0022847
         c15 |  -.0070733   .0013326    -5.31   0.000    -.0096851   -.0044615
        size |   .0001624   .0004914     0.33   0.741    -.0008008    .0011255
       _cons |   .0075275    .004514     1.67   0.095    -.0013197    .0163747
-------------+----------------------------------------------------------------
         rho |   .6039208
------------------------------------------------------------------------------
```

Figure B.3: Stata regression output Model 2 controlling common AR(1)

```
. xtpcse IM LR d07-d11 c15 size, c(p) het
(note: estimates of rho outside [-1,1] bounded to be in the range [-1,1])

Prais-Winsten regression, heteroskedastic panels corrected standard errors

Group variable:   bank                        Number of obs      =       299
Time variable:    year                        Number of groups   =        50
Panels:           heteroskedastic (unbalanced) Obs per group: min =         5
Autocorrelation:  panel-specific AR(1)                       avg =      5.98
                                                             max =         6
Estimated covariances      =        50        R-squared          =    0.5879
Estimated autocorrelations =        50        Wald chi2(8)       =    164.48
Estimated coefficients     =         9        Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |           Het-corrected
          IM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          LR |    .102597   .0581879     1.76   0.078    -.0114493    .2166432
         d07 |  -.0001405   .0007508    -0.19   0.852     -.001612    .0013309
         d08 |   .0015886   .0010028     1.58   0.113    -.0003769    .0035542
         d09 |   .0008482   .0010867     0.78   0.435    -.0012817    .0029782
         d10 |   -.000613   .0011865    -0.52   0.605    -.0029384    .0017125
         d11 |  -.0009279   .0012944    -0.72   0.473    -.0034648    .0016091
         c15 |  -.0070252   .0010981    -6.40   0.000    -.0091774   -.0048731
        size |   .0001924   .0003926     0.49   0.624    -.0005771    .0009619
       _cons |   .0084381   .0038769     2.18   0.030     .0008394    .0160367
-------------+----------------------------------------------------------------
      rhos =  .7468598 -.0757153         1 -.2123531 -.2225956 ...   .8041649
------------------------------------------------------------------------------
```

Figure B.4: Stata regression output Model 2 controlling panel-specific AR(1)

Appendix C

Appendix Section 4.5

C.1 Robustness Check Specification (1)

```
. xtpcse PD LR d07-d11 c3 loans IFRS, c(a) het
(note: estimates of rho outside [-1,1] bounded to be in the range [-1,1])

Prais-Winsten regression, heteroskedastic panels corrected standard errors

Group variable:   bank                          Number of obs      =       291
Time variable:    year                          Number of groups   =        51
Panels:           heteroskedastic (unbalanced)  Obs per group: min =         2
Autocorrelation:  common AR(1)                                 avg =  5.705882
                                                               max =         6
Estimated covariances      =        51          R-squared          =    0.3875
Estimated autocorrelations =         1          Wald chi2(9)       =    115.73
Estimated coefficients     =        10          Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |           Het-corrected
          PD |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          LR |   .0473666   .0154378     3.07   0.002     .0171092    .0776241
         d07 |  -.0023149   .0152723    -0.15   0.880    -.0322481    .0276182
         d08 |   .0533484   .0168825     3.16   0.002     .0202593    .0864376
         d09 |    .142077   .0170891     8.31   0.000      .108583    .1755709
         d10 |   .0088219   .0171639     0.51   0.607    -.0248188    .0424625
         d11 |   .0341279   .0170124     2.01   0.045     .0007843    .0674715
          c3 |   .2525147   .0895019     2.82   0.005     .0770941    .4279353
       loans |   .0000328   .0000169     1.94   0.052    -3.26e-07     .000066
        IFRS |  -.0422255   .0326787    -1.29   0.196    -.1062747    .0218236
       _cons |   .0209984   .0332194     0.63   0.527    -.0441104    .0861071
-------------+----------------------------------------------------------------
         rho |   .1549299
------------------------------------------------------------------------------
```

Figure C.1: Robustness check specification (1) Model 1

```
. xtpcse IM LR d07-d11 c15 size IFRS, c(a) het
(note: estimates of rho outside [-1,1] bounded to be in the range [-1,1])

Prais-Winsten regression, heteroskedastic panels corrected standard errors

Group variable:   bank                          Number of obs      =       299
Time variable:    year                          Number of groups   =        50
Panels:           heteroskedastic (unbalanced)  Obs per group: min =         5
Autocorrelation:  common AR(1)                                 avg =      5.98
                                                               max =         6
Estimated covariances      =        50          R-squared          =    0.2080
Estimated autocorrelations =         1          Wald chi2(9)       =    130.75
Estimated coefficients     =        10          Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |           Het-corrected
          IM |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          LR |   .1298039   .0632358     2.05   0.040     .0058641    .2537437
         d07 |  -.0003267   .0009796    -0.33   0.739    -.0022466    .0015932
         d08 |   .0017925    .001225     1.46   0.143    -.0006084    .0041934
         d09 |   .0012391   .0013028     0.95   0.342    -.0013142    .0037925
         d10 |  -.0001823   .0013912    -0.13   0.896     -.002909    .0025443
         d11 |  -.0005981    .001469    -0.41   0.684    -.0034774    .0022811
         c15 |  -.0066978   .0012037    -5.56   0.000    -.0090571   -.0043385
        size |   .0000236    .000508     0.05   0.963     -.000972    .0010193
        IFRS |  -.0031572   .0030969    -1.02   0.308    -.0092271    .0029127
       _cons |   .0113806   .0066937     1.70   0.089    -.0017387    .0244999
-------------+----------------------------------------------------------------
         rho |   .5974618
------------------------------------------------------------------------------
```

Figure C.2: Robustness check specification (1) Model 2

C.2 Robustness Check Specification (2)

```
. xtpcse PD LR loans d07-d08 c3, c(a) het
(note: estimates of rho outside [-1,1] bounded to be in the range [-1,1])

Prais-Winsten regression, heteroskedastic panels corrected standard errors

Group variable:   bank                          Number of obs      =       150
Time variable:    year                          Number of groups   =        51
Panels:           heteroskedastic (unbalanced)  Obs per group: min =         2
Autocorrelation:  common AR(1)                                 avg =  2.941176
                                                               max =         3
Estimated covariances      =        51          R-squared          =    0.3622
Estimated autocorrelations =         1          Wald chi2(5)       =     80.63
Estimated coefficients     =         6          Prob > chi2        =    0.0000

------------------------------------------------------------------------------
             |           Het-corrected
          PD |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          LR |   .0375048    .007453     5.03   0.000     .0228972    .0521125
       loans |   .0000358   .0000162     2.21   0.027     4.00e-06    .0000676
         d07 |  -.0019735   .0085113    -0.23   0.817    -.0186553    .0147083
         d08 |   .0539429   .0076191     7.08   0.000     .0390098     .068876
          c3 |   .0264533   .0138218     1.91   0.056     -.000637    .0535435
       _cons |  -.0094533   .0059936    -1.58   0.115    -.0212005    .0022939
-------------+----------------------------------------------------------------
         rho |  -.2293839
------------------------------------------------------------------------------
```

Figure C.3: Robustness check specification (2) Model 1

C.3 Robustness Check Specification (3)

```
. xtpcse interestinc LR d07-d11 c15 size, c(a) het

Number of gaps in sample:  1
(note: computations for rho restarted at each gap)
(note: estimates of rho outside [-1,1] bounded to be in the range [-1,1])

Prais-Winsten regression, heteroskedastic panels corrected standard errors

Group variable:   bank                          Number of obs      =       246
Time variable:    year                          Number of groups   =        43
Panels:           heteroskedastic (unbalanced)  Obs per group: min =         2
Autocorrelation:  common AR(1)                                 avg =   5.72093
                                                               max =         6
Estimated covariances      =        43          R-squared          =    0.3656
Estimated autocorrelations =         1          Wald chi2(8)       =    104.69
Estimated coefficients     =         9          Prob > chi2        =    0.0000
```

interestinc	Coef.	Het-corrected Std. Err.	z	P>|z|	[95% Conf.	Interval]
LR	.145942	.0679767	2.15	0.032	.01271	.279174
d07	.0042106	.0015019	2.80	0.005	.0012669	.0071544
d08	.0083172	.0019488	4.27	0.000	.0044975	.0121369
d09	-.0025881	.0021589	-1.20	0.231	-.0068195	.0016433
d10	-.0057751	.0023144	-2.50	0.013	-.0103111	-.001239
d11	-.0049451	.0024508	-2.02	0.044	-.0097485	-.0001417
c15	-.0158047	.0030843	-5.12	0.000	-.0218498	-.0097596
size	.0004414	.0006583	0.67	0.502	-.0008488	.0017316
_cons	.0169697	.0055159	3.08	0.002	.0061588	.0277806
rho	.6576561					

Figure C.4: Robustness check specification (3) Model 2

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