Aspects of Stability in the Financial Sector

D I S S E R T A T I O N
of the University of St. Gallen,
School of Management,
Economics, Law, Social Sciences
and International Affairs
to obtain the title of
Doctor of Philosophy in Management

submitted by

Matthias Schaller

from

Germany

Approved on the application of

Prof. Dr. Beat Bernet

and

Prof. Dr. Martin Brown

Dissertation no. 4177

printy A. Wittek GmbH, München 2013

The University of St. Gallen, School of Management, Economics, Law, Social Sciences and International Affairs hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St. Gallen, May 17, 2013

The President:

Prof. Dr. Thomas Bieger

Acknowledgements

With a total of five different co-authors, I can hardly claim this dissertation to be my own work. Thank you Martin, Markus, Stefan, Sue, and Simone (sorted by family names) for the valuable and constructive discussions and even more for any parts written by any of you that made its way to this manuscript. Thank you Beat and Martin not only for supervising my dissertation, but also for having me at each of your chairs. Being the last of Beat's and the first of Martin's internal Ph. D. candidates was a great opportunity. I also want to thank Matthias for the virtual workout at the office and also for sharing his extensive knowledge about the inner workings of the HSG-Administration. Thank you, Pascale, Beatrix, and Benjamin for all the support whenever needed and also for the nice chats that lightened up my days. Thank you, Stefan for the good teamwork in what amounts to, at least in my recollection, seven lectures you held and I assisted. I also want to add an additional special thanks to Simone for providing the luxury company retreat for the frugal summer vacationist.

Mom and dad, I want to thank you for your loving care, for the possibility to learn and study the first three decades of my life, and for teaching me what is truly important in life.

I also want to thank my brother, my sister, and Hilde for taking such good care of each other and for the great time we have whenever we are together. Thanks also to the rest of my family and all my friends I met during school or while studying. Without all of you, the past years would have been a lot less enjoyable.

Anne, most of all I want to thank you! I want to thank you for your patience and your love, for your kindness and support, for taking me to foreign countries and also for spending cold winter days eating pizza and watching TV. I can't wait for the next adventure to start!

You are the love of my life.

Table of Contents

List of Figures

List of Tables

Abstract

This dissertation presents four essays on different aspects of stability in the financial sector. The first paper, (i) analyses to what extent loan officer use their discretion to smooth credit ratings of their clients, and (ii) whether this use of discretion is driven by information about the creditworthiness of the borrower or by the insurance of clients against fluctuations in lending conditions. Our results show that loan officers make extensive use of their discretion to smooth clients' credit ratings. The use of discretion by loan officers seems driven by their reluctance to communicate price changes rather than by superior information.

In the second paper, we test how control over loan officers affects their discretionary assessment of clients in small business lending. Our results show that, loan officers assign consistently more positive credit ratings under control. Loan officers learn from their experience under control and assign more positive ratings if they (i) are more experienced and (ii) were frequently corrected in the past. Our results further indicate that the use of control does not increase the efficiency of the rating tool. From a cost-perspective, the use of control is even clearly inferior.

In the third paper, we compare liquidity patterns of 10,979 failed and non-failed US banks from 2001 to mid-2010 and detect diverging capital structures: Failing banks change their liquidity position about three to five years prior to default by increasing liquid assets and decreasing liquid liabilities. By abandoning (positive) term transformation, failing banks drift away from the traditional banking business model. We show that this liquidity shift is induced by window dressing activities towards bondholders and money market investors as well as a bad client base.

In the last paper, we develop an innovative approach for the risk-adjusted pricing of deposit insurance premiums. Models for the pricing of deposit insurance premiums either use expected loss approaches or Merton-based option pricing methods. We present a methodology to allocate deposit insurance premiums among financial institutions that uses elements of both approaches: We use standard key figures on capitalization and liquidity from expected loss models and integrate these figures into a stochastic process based on the Merton framework. We are able to build on the advantages of a multi-indicator model while still using the dynamic information of option pricing models.

Abstract in German

Die vorliegende Dissertation enthält vier Arbeiten zu unterschiedlichen Aspekten der Stabilität von Finanzsektoren. In der ersten Studie zeigen wir, dass Kundenbetreuer ihren Bewertungsspielraum nutzen, um Kreditratings ihrer Kunden über die Zeit zu glätten. Unsere Ergebnisse belegen ferner, dass dieses Verhalten nicht von zusätzlicher Information getrieben wird. Während das Verhalten so aussieht, als würde die Bank den Kunden eine implizite Versicherung gegen Zinsschwankungen bieten, ist es tatsächlich allerdings vermutlich eher so, dass Kundenbetreuer hauptsächlich scheuen, Kreditverträge neu zu verhandeln.

In der zweiten Studie zeigen wir, dass Kundenbetreuer dazu neigen, ihren Bewertungsspielraum zu nutzen, um Kunden bessere Ratings zu erteilen, wenn diese Ratings später von einer weiteren Person kontrolliert werden. Dieses Verhalten ist umso stärker, je erfahrener ein Kundenbetreuer ist und je öfter sein Rating bei vorhergehenden Anträgen korrigiert wurde. Wir können ferner zeigen, dass die Kontrolle von Kundenbetreuern nicht zu effizienteren Ratings führt. Aus einer Kostenperspektive sind solche Ratingprozesse sogar deutlich unterlegen.

In der dritten Arbeit vergleichen wir die Entwicklungen in der Liquiditätsstruktur von US-Amerikanischen Banken. Banken, die während des Beobachtungszeitraums insolvent werden, erhöhen den Anteil liquider Aktiva etwa drei bis fünf Jahre vor ihrem Ausfall, während der Anteil liquider Passiva verringert wird. Durch die Aufgabe der (positiven) Fristentransformation schweifen diese Banken vom traditionellen Geschäftsmodell der Banken ab. Die Veränderungen zielen darauf ab, sich gegenüber den Besitzern von Anleihen und Geldmarktinvestoren in ein gutes Licht zu rücken. Zusätzlich ist eine schlechtere Kundenbasis ein treibender Faktor dieser Entwicklung.

In der letzten Arbeit entwickeln wir schliesslich eine Methodik, Risiko-adjustierte Einlagensicherungsprämien zu berechnen. Unsere Methodik erlaubt es, die beiden relevanten Ansätze zur Berechnung von Einlagensicherungsprämien (Ansätze basierend auf erwarteten Verlusten und Merton-basierte Optionspreismodelle) zu vereinen. Wir integrieren Standard-Kennzahlen zur Kapitalisierung und Liquidität von Banken in einen stochastischen Prozess und sind so in der Lage die Vorteile des Multi-Indikator Models zu nutzen ohne die dynamischen Informationen eines Optionspreismodells zu verlieren.

“If you knew what you were doing it wouldn’t be called research"

~Albert Einstein

1. *When the Music Stops Playing...*

Among many others, two changes in the markets substantially fuelled the financial crisis: First, market participants did no longer trade one particular asset and instead started trading different classes of supposedly homogenous assets. If you would want to buy flowers, this translates into switching from "I would like to buy exactly this tulip over here" to "I would like to buy one of your violet tulips". Second, market participants did no longer trade single assets, but whole bundles of assets with supposedly similar characteristics ("I would like to buy a dozen of your violet tulips"). Markets that are based on the trading of bundled assets with standardized specifications potentially attract speculators if, in addition, market prices show strong positive momentum. These speculators are typically neither very skilled in the assessment of the traded assets nor are they interested in the asset by itself. This is also why it is not profitable for a speculator to try buying exceptionally beautiful or exceptionally cheap tulips just for the purpose of reselling it - which is pretty much what a florist does. When tulip prices steadily increase, however, speculators are able to simply rely on the momentum by buying the tulip and reselling it at a higher price in the near future. As speculators do not know if one particular tulip is more valuable than the other, this approach is only profitable if markets trade "dozens of violet tulips" rather than one particular tulip. And this is exactly what markets did…

…tulip markets in the Netherlands of the beginning 17th century.

What sounds like an illustration of the market dynamics during the onset of the recent financial crisis is a story about tulips: On February 5th 1637, the most expensive tulip ever, an Admirael van Enchhysen, was sold at an auction in Alkmaar, Netherlands, for 5´200 guilder - an amount equivalent to the average salary for 34 years of work (Goldgar 2007). For two of these tulips, you could buy a house in one of the most luxurious neighbourhoods in the city-centre of Amsterdam (Segal 2004). Of course, even at that time, nobody thought the intrinsic value of a tulip to be anywhere close to its actual price. The buyer was simply the last one in a long line of financial speculators buying tulips in the prospect of finding someone else whom to resell it to at a higher price. A business that made many people very rich, before eventually, when no new market entrants pushed prices further up, the music stopped playing. The unfortunate last-in-line who did not find the proverbial empty chair to sit on, was left with tulips he never intended to actually own and had absolutely no use for (other than reselling them). When speculators realized that prices were no longer rising, they immediately started flooding the market with tulip offerings and prices crashed to values a fraction of their peak quotations – but much more reasonable.

What is now known as the “Tulipmania” is the first well-documented incident of a price bubble in financial markets that keep threatening financial stability even today. Ever since, price bubbles are a recurring phenomenon in financial markets. Just as the Tulipmania, many bubbles start in markets that show steadily increasing asset prices for a period longer than the market participant can remember - which is surprisingly short yet every time again. Tulip prices, at that time, rose because the richer parts of the population in Europe simply liked having tulips in their gardens and frontyards. Tulips were hard to grow in most of Europe and had to be imported from Turkey to a large extent, making them an expensive luxury good. When tulips became more and more popular and wealth increased among the population, allowing ever more people to afford luxury, the growing demand for tulips steadily pushed prices up. When prices rose long enough, people got the impression that tulips actually could be a highly profitable investment. And the music started playing...

2. *How Ninjas Killed the Lehman Brothers*

When the first of what are now two consecutive financial crises began to unfold in the late 2000s, it did not take long for the financial crisis to develop into an economic disaster. Financial crises are different from crises in other industries for the exact same reason: The financial sector is such a pivotal element in modern economies that problems within this sector almost indivertibly spill-over to other industries, households, and the public sector. But what makes the financial sector so special?

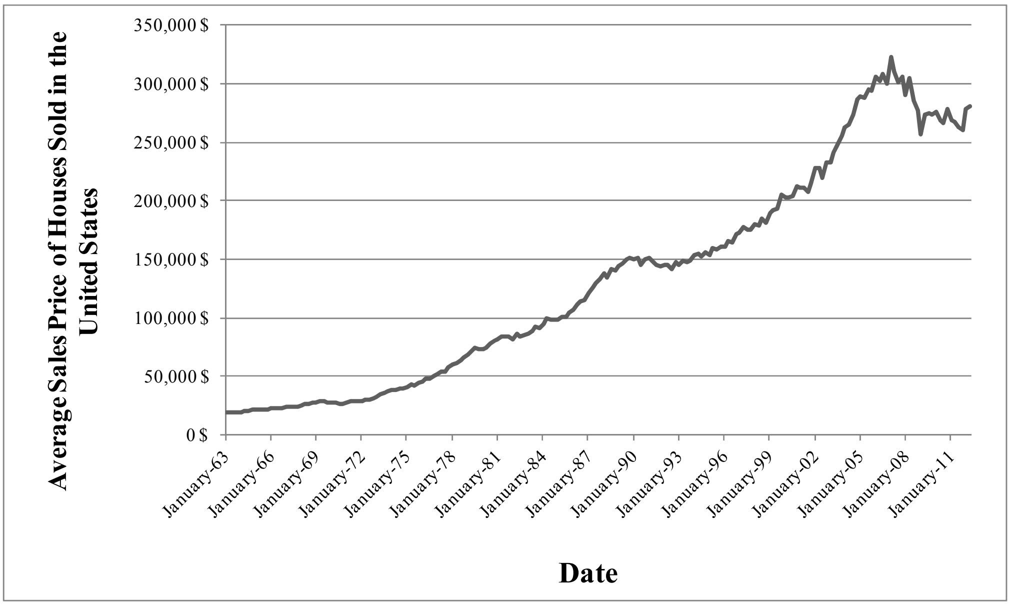
Financial endowments and investment opportunities within an economy are distributed across entities as well as over time. The problem is that both distributions do not necessarily converge. Financial intermediaries accumulate excess capital from market participants with excess funds and lend it to market participants with investment opportunities but no available capital. In order to incentivize potential lenders to participate in this re-allocation process, the recipients of the loans repay them with a premium - the interest. The bank, after deducting a compensation for its effort, channels the remainder to the lender. This transformation function of financial intermediaries increases the welfare of the entire economy by providing a more efficient use of the available capital at any point in time (Rochet 2008).

Of course, potential borrowers could also try to find matching lenders on their own and hence circumvent the additional interest payments charged by the bank. However, as individual lending and borrowing offers hardly match perfectly, banks are able to reduce overall transaction costs. Without banks, a potential lender would need to screen any potential investment opportunity not only for the likelihood of success (and the repayment of the loan), but also for matching maturities and investment sizes. Financial intermediaries facilitate this process by pooling funds and lending to a diversified pool of borrowers. The bank and the law of large numbers are then able to allow lenders to deposit with or withdraw from the bank exactly as they need to. By subtracting a small share from all interest payments to lenders for the average default probability, the bank is even able to repay any particular deposit unconditionally on the success of a specific investment.

This increase in ease and efficiency of financial markets, however, depends on the financial intermediaries granting loans only (or mostly) to applicants that have a profitable investment opportunity and are therefore likely to repay. While diversification and the equity of banks provide some cushion to the degree of bad investment decisions a bank is allowed to make, these cushions hardly hold against any systemic changes in the banks' risk assessment and the appetite for risk of financial intermediaries. In the early years of the 21st century, when economies steadily recovered from the bust of the dotcom-bubble and people were looking for profitable investment opportunities, financial intermediaries turned to private real estate where they were observing soaring house prices. More importantly though, house prices appeared not only to be rising ever faster, they had done so for quite some time without major setbacks (see Figure 2-1).

Figure 2-1: Average Sales Price of Houses Sold in the United States

This figure plots the average nominal sales price in US-Dollar of residential houses in the USA. The data is collected by the US Department of Commerce on a quarterly basis for the period January 1963 to March 2012.



Source: US Department of Commerce

Soon, people in the financial industry agreed on the hypothesis that real estate prices in highly developed financial markets should in fact be rising. While the long-term increase of nominal per capita income does in fact imply the notion of increasing real estate prices in the long run, the strong attention for real estate as a financial investment during that period can rather be attributed to a "new-era" effect associated with the exploding house prices during the first years of the new millennium. When real estate prices rose at very high rates every year again, more and more investors as well as households started to believe that this boom is not really a boom but the result of a change in market conditions that justifies higher returns on house prices in the long run – a new era (Shiller 2012). Sound or not, the assumption that (private) real estate is the safe haven of financial investments opened up new doors to the financial industry. The adventurous financial engineers stormed these doors and started constructing new and complex financial products that allowed many new target groups with very different investment philosophies to participate in the boom of real estate prices. Taking ever-rising home prices for granted, defaults on mortgages should remain on constantly low levels over time. This put securitization products on the forefront of financial innovation. Securitization of mortgages had two major selling points in this market environment: On the supply side, it allowed banks to sell any part of their otherwise illiquid mortgage portfolio on the market. On the demand side, by pooling mortgages and slicing them into several tranches with differing risk-return profiles, securitization, supposedly, was able to create an investment asset that makes up the largest part of your mortgages in overall volume but is essentially risk-free (according to rating agencies).

The market for investments with very low risk is huge and hence, investment advisors were immediately captured by the idea of almost risk-free profits. Investors at pension funds embraced securitization products because they offered the possibility to earn marginally higher returns than other risk-free assets, like sovereign debt, while still meeting their highly conservative investment criteria. From a scientific point-of-view, securitization was a great tool as it offered the possibility to more efficiently distribute credit risk within markets (Rajan and Zingales 2003, Shiller 2003). There were, however, at least two major flaws in the assessment of securitization products at the time: Rating agencies typically assigned the risk-free label to the safest tranche, irrespective of the underlying pool of mortgages. The problem is, many mortgages with very low quality still remain mortgages with very low quality if you pool them together. As it turns out, garbage-in-garbage-out beats diversification. Second, scientists, prominently represented by Raghuram Rajan (2010), drew their conclusions ceteris paribus *"that is, assuming that everything else but the phenomenon being studied, in this case securitization, remained the same. Typically, everything does not remain the same."* Markets reacted on the changing incentive schemes that securitization posed. While securitization might help improving market efficiency ceteris paribus, it did not do so because banks were lowering credit standards in response to increasing competition and the possibility of selling any part of their credit portfolio to the market. In the end, markets were getting even riskier over time and not the other way around (Rajan 2010).

Looking at the developments from the supply side, even though the boom in real estate markets throughout the USA provided a steady supply of new real estate loans to securitize, the demand especially for the triple-A chunks of mortgage-backed securities was so large that banks soon had to think of new and underdeveloped markets. With the benefit of hindsight, it is safe to say that it should have been obvious that something goes terribly wrong when the NINJA's conquered the mortgage markets: No Income, No Job, no Assets. The acronym that turned into the synonym for financial folly during the subprime crisis reflects the infamous masterpiece in the relaxation of credit standards. When everybody who could afford a house and - more importantly - a mortgage, already had one, credit originators in the USA had to turn to the part of the population that, under any previous assessment, was in no position to afford a property.

The mortgages targeting the NINJA-segment were constructed to require no initial payment and no or hardly any repayments during the first years of the mortgage. From a marketing perspective, these subprime mortgages were tailored to the needs of a sizeable and underdeveloped business segment. On the downside, the design of these mortgages turned them into time bombs for whoever ended up owning them. The fuse took approximately two years to burn down, which is approximately the end of the teaser period of these mortgages. At this point, amortization payments start and fixed interest payments turn into floating payments that not only properly reflect the low creditworthiness of a typical NINJA, but also make up for the low interest payments in the first years. While it was relatively easy to sell a subprime mortgage as part of a mortgage-backed security, it was distinctively harder to collect all the contractually agreed-upon payments as the borrowers simply did not have any significant assets other than the real estate itself. Conveniently enough, some of the mortgage contracts stipulated that, if you are no longer able to meet your obligations and you decide to default on your loan, you simply evict the property and mail the keys to your bank. As mortgages in most US-American states restrict the homeowners' liability to the collateral, defaulting on a mortgage is the quick and easy solution if you are no longer able to repay the loan and you want to save you and the bank the trouble of eviction. Under these conditions, however, defaulting is also a rational and very likely solution if the value on your home declined during the teaser period and you did not yet invest any significant amount of money for a down payment or any amortization payments.

While, depending on the legal and personal situation, borrowers acted more or less rationally when they accepted the opportunities presented by the financial sector, the remaining question is: Why did banks offer these loans in the first place? Basically, the mortgage business of a bank is quite simple. Someone applies for a loan, the bank assesses the creditworthiness of the potential customer, and the bank either does or does not grant a loan. The bank realizes a profit if the customer repays the mortgage. The bank makes a loss if the borrower defaults. From an incentive point-of-view, this process as a whole is very efficient because it forces the banks to diligently screen its customers and properly assess their creditworthiness, as the banks are also the ones directly affected by any losses. Preceding the financial crisis, however, banks started to dissect this process: The mortgage originator acquires the borrowers, but then sells the mortgage to the bank (or even made the loan on the account of the bank). The bank can either keep the mortgages on its own balance sheet, or it can sell them as securitized products. The mortgage originator is usually paid based on the newly contracted mortgage volume and is hence mainly interested in originating as many loans as possible but not necessarily in distinguishing good borrowers from bad borrowers. The bank's incentives to screen or monitor its mortgages diminish by the degree that mortgages in its portfolio are securitized, simply because losses of these mortgages do not affect the bank any more. Investors in mortgage-backed securities are hardly interested in monitoring the underlying mortgages as well. As they acquire a whole pool of mortgages with some average credit quality they simply rely on the diversifying effect of the large number of debtors. In the end, securitization could have helped increasing the efficiency in the risk allocation within the financial market. What it actually did, however, was to significantly decrease the incentives to screen and monitor mortgage customers. The results were increasing incentives to systematically lower credit standards and an overall decrease in the average quality of mortgages in the whole economy.

Information or Insurance? The Role of Loan Officer Discretion in Credit Assessment

In the end, the inefficient design of the mortgage process led to worsening credit portfolios within the whole financial sector. Inefficiently designed mortgage processes and skewed incentive schemes at the onset of the financial crisis are the latest proof that even the "conservative" loan business is of vital importance for the stability of the financial sector. In the first study, co-authored with Martin Brown, Simone Westerfeld, and Markus Heusler, we intend to gain a better understanding of how to efficiently design this loan process. In particular, this study examines whether the current design of rating models is able to effectively incorporate the available information into the rating outcome, especially if a customer experiences a shock to its observable creditworthiness, e.g. during a crisis.

Good Cop or Bad Cop – Does Control Lead to More Efficient Credit Assessments or Crowd-Out Loan Officer Motivation in Small Business Lending?

Following up on the first project, the second closely related study focuses on the same general topic targeting the efficient design of loan processes. Regulatory frameworks, most importantly Basel II, stress the importance of bank-internal credit ratings. These internal credit ratings typically employ a statistically optimized credit rating model, with a loan officer responsible for collecting all relevant information. Currently, experimental and empirical predictions arrive at opposing recommendations regarding the use of control within this process. The second study disentangles these findings by not only providing evidence for the optimal use of control within credit applications, but also by presenting new insights that might help explaining the existing differences in current studies.

The skewed incentive schemes led to a gradual decrease of the average quality in the mortgage pool over time. Even though securitization helped scattering the risky mortgages across many different investors, the overall decrease in average credit quality was large enough to pose a severe threat to the stability of financial sectors. When fixed interest rates were converted into much higher floating rates, many borrowers in the subprime segment defaulted immediately. With the spike in foreclosures, market prices for private real estate started their decline. This, in turn, not only diminished the incentives for the remaining borrowers to repay their mortgages, but also decreased the values of the remaining real estate as collateral. With increasing mortgage defaults and decreasing collateral values, banks started to realize heavy losses on both, their mortgage portfolio and their investments in mortgage-backed securities. As banks were systematically engaged in subprime credit and mortgage-backed securities, banks were also systematically suffering from the crisis on the real estate markets.

The interbank market - the market where banks lend each other money on a short-term basis – connects banks to each other. On the interbank market, each bank may either be a debtor or a creditor, depending on whether a bank needs to store or borrow cash on that particular day. Even though this market is very important for banks to be able to operate efficiently, it solely builds on trust, as short-term interbank loans are typically not collateralized. At the beginning of the subprime crisis, banks were engaged in subprime mortgages to different degrees. Accordingly, banks were also differently strong affected by the increasing number of defaults in mortgage markets. As banks, however, are very opaque businesses, it is relatively hard to assess, even for other banks, whether or not a bank is in a sound condition. As banks are aware of this problem, when they feel that there is a systematic problem in the industry, they start to mistrust each other. When mistrust is sufficiently large, banks stop lending each other money on this uncollateralized basis and interbank markets freeze up. Banks also rely on the interbank market to different degrees. Investment banks, without the possibility to accumulate deposits, are at the top end. In this light, it is no wonder that, during the subprime crisis, investment banks were also the first to experience fatal liquidity problems culminating in the takeover of Bear Stearns and the failure of Lehman Brothers on September 15th 2008.

Liquidity Dynamics of Bank Defaults

A bank is the more vulnerable to the freeze-up of interbank markets, the more it depends on that particular market for its refinancing needs. If banks would want to insure themselves against fluctuations in the availability of interbank funds, they simply need to hold more cash. As it was becoming increasingly clear that, during the subprime crisis, banks were suffering not only from credit losses, but also from the drainage of interbank liquidity, requiring more cash holdings was also the immediate reaction of politicians and regulators. Holding cash, however, is very expensive and it is hard to say what the sweet spot for a liquidity cushion is. In the third project, Stefan Morkötter, Simone

Liquidity Dynamics of Bank Defaults

Westerfeld, and I, hence try to shed some light on the question if holding more liquid assets does in fact save banks from failure in crisis periods. Using accounting data of US-American banks, we analyse (i) whether banks that eventually default, show a different liquidity structure in their balance sheet than their stable peers and (ii) what drives any observed differences in the liquidity structure.

What were the consequences from the default of Lehman Brothers? When Lehman Brothers failed, the fear was that its interconnectedness with other financial institutions would lead to a domino-effect of even more bank failures. And, while financial institutions did in fact tremble and some of them even fall, depositors remained relatively calm and, most importantly, did not engage in any significant bank-runs. Abstracting from any security schemes, a bank-run, i.e. depositors running at their banks in order to withdraw their available funds, is one of the equilibriums in an economy where depositors have no perfect knowledge about the condition of their bank (Diamond and Dybvig 1983). Since term transformation, i.e. transforming short-term liabilities into long-term assets, is one of the key functions of the banking business model, banks do not have sufficient cash available to redeem all of their deposits at a time. Banks rather rely on the diversified need for cash among their depositors, meaning that not all depositors will need its deposits at the same time. If depositors, however, suspect the bank to be in financial distress, depositors do not withdraw their funds based on individual needs but because they fear that they might not get their money back in the future. In this case, with most of the bank's assets caught up in illiquid assets, the cash of the bank quickly depletes, irrespective of whether or not the bank was actually in trouble or not. For each depositor, it is therefore the optimal strategy to run at the bank if he or she suspects the other depositors to do so as well.

In the recent financial crisis, however, there were hardly any bank-runs. Bank runs are caused by depositors that fear that they will not be repaid in the future. To remedy this fear, regulatory authorities insure depositors against losses to their deposits and, if a bank is not able to repay its deposits, the deposit insurance scheme stands up for the claim. If the deposit insurance scheme is credible, a panic resulting in a bank-run is no longer a potential equilibrium. During the subprime crisis, trust in the deposit insurance scheme in the USA, in fact, went so far that not even the depletion of available funds in the deposit insurance fund led to problems with increasing deposit withdrawals.

An Alternative Way of Calculating Risk-based Deposit Insurance Premiums

Deposit insurance schemes worked and did what they were designed for: Prevent bank-runs. What is all but clear is, how to efficiently charge the banks for this insurance. From a theoretical perspective, premium charges should be based on the risk each bank poses to the insurance scheme. It is still in question, however, how to actually measure this risk. In the fourth study, Susanna Walter and I develop a calculation method for such a risk-adjusted pricing scheme. We combine aspects of the two most common approaches for calculating risk-adjusted deposit insurance premiums: Expected-loss pricing and Merton-based pricing methods. While our methodology relies only on observable information, which is the major shortcoming of common Merton models, we are able to keep the dynamic mechanics of the option-pricing methodology.

Even without bank runs and even though governments took resolute action in order to stabilize the financial sector, the US-subprime crisis not only caused severe economic trouble by itself, it also made its transition to the European sovereign-debt crisis. Government assistance to financial institutions coupled with decreasing tax revenues ignited the explosion of budget deficits and public debt in most European countries. In addition, governments in the European monetary union no longer had the option to devalue public debt by increasing inflation levels and trade imbalances increased as more productive economies within the union were able to benefit from artificially low exchange rates. As it turns out, in the end, the ninjas might not only have killed the Lehman Brothers, but might also have assisted in killing the piigs...

3. *Theories of Stability in the Financial Sector*

3.1. What is Stability in the Financial Sector?

Stability of the financial sector is not only a major goal of governments, regulators, and central banks around the world; it is also a subject that captures a significant amount of scientific resources for quite some time. As pointed out in the introduction and also in Reinhard's and Rogoff's (2009) account of financial crises in the past, the topic is around for several centuries. But what exactly is stability of the financial sector? Definitions approach the question from two different angles: First, a stable financial sector is characterized by the absence of a crisis. Second, a stable sector needs to be able to perform its key economic functions efficiently (e.g. Mishkin 1999; Deutsche Bundesbank 2003; Norwegian Central Bank 2003).

A financial crisis can either affect a single financial institution, which is also referred to as the micro-prudential dimension of financial stability, or as a systemic crisis affect the financial sector as a whole; the macro-prudential dimension of stability (Crockett 2000). While, naturally, systemic crises have been at the centre of academic as well as public attention, crises to single financial institutions are also able to pose a serious threat to an economy. Historically, several systemic crises were initially triggered by a single and by itself insignificant incident that spread out across the whole sector. The Herstatt crisis in Germany is just one example where the eponymous incident is the collapse of a small private bank.

Theory distinguishes between two types of systemic crises leading to two different sets of problems: Panic-induced systemic crises and crises caused by negative economic prospects. A systemic crisis that is triggered by the fall of a single financial institution typically tends to be associated with a panic. Characteristically, financial institutions that suffer from a systemic crisis, default due to illiquidity rather than insolvency (e.g. Friedman and Schwartz 1963; Kindleberger 1978). The second kind of systemic crisis results from a negative outlook regarding the future economic development. Depositors might fear that banks are more likely to fail because of an anticipated increase in loan defaults and might hence not be able to repay their depositors in the future. During this sort of crisis, banks usually default due to insolvency (Mitchell 1941).

Micro- and macro-prudential dimensions of financial stability can also be categorized based on the differences in their goals. The macro-prudential objective intends to limit the costs that result from any sort of distress to the financial sector as a whole. It hence focuses on and tries to limit the systemic part of risk in to the financial sector. Accordingly, a large part of macro-prudential stability focuses on correlated probabilities of failure between different financial institutions. In contrast, the micro-prudential dimension of financial stability aims at limiting the probability of default for every participant in the financial market. Micro-prudential regulation, therefore, does not incorporate correlations, but assesses the idiosyncratic risk. The major goal here is the minimization of the costs to depositors resulting from individual bank failure (Crockett 2000).

3.2. Measuring Stability in the Financial Sector

While the definition of financial stability is relatively vague, researchers have come up with quite distinct approaches answering a closely related question: How to measure stability in the financial sector? Again, common approaches distinguish between measuring micro-level stability and macro-level stability. On the individual bank level, a crisis, and hence the absence of stability, is usually determined using some measure of a bank's proximity to default. Approaches differ in their complexity and granularity: The simplest and least exact way measures the proximity to default as a binary choice, resulting in the actual legal default of a bank as relevant criterion. More accurate approaches not only differentiate between default and no default, but rather allocate financial institutions a value indicating its likelihood of failure in the future. The most common approach uses the z-score. The z-score in its original setup was introduced by Altman (1968). He uses a multivariate regression to assign companies a score based on their likelihood of becoming financially distressed in the future. In that sense, the z-score is the ancestor to most current credit rating models. The original Altman-approach, however, does not focus on the peculiarities of the financial industry but rather assesses the stability of any kind of business. In a more bank-specific approach, Boyd et al. (2006) express the z-score as the sum of the capital-to-asset ratio and the return-on-assets weighted by the standard deviation of the return on assets. The result indicates how many standard deviations in return of assets a bank is away from bankruptcy. The technical details of assessing bank fragility are moderately well understood. The difficulties with these models arise from the fact that most advanced models rely on non-linear regressions and require a large number of actual bank failures for a proper calibration. While this might be more or less feasible for some countries[1], most economies do not experience bank failures on a regular basis.

Approaches for the determination of systemic banking crises typically use a combination of several indicators. Demirguc-Kunt and Detrigiache (1998, 2002), for example, assess the financial sector to be in a systemic crisis if: (1) non-performing assets reach 10% of total assets, (2) rescue cost for an economy reach at least 2% of the gross domestic product, (3) significant emergency measures were taken (e.g. bank holidays), or (4) large-scale bank nationalizations were executed. It is obvious that any of these criteria is highly arbitrary in, at least, the choice of the respective cut-off values. Nevertheless, Honohan and Laeven (2005), using the aforementioned criteria, find 116 crises in 113 countries for the period between 1974 and 2002. In alternative approaches, Friedman and Schwartz (1963), Caprio and Klingebiel (1997), and IMF (1998) use deposit runs to identify banking crises. Taking the lack of bank-runs in the current financial crises into account, this approach, however, might not be very promising for the assessment of future crises. Lindgren et al. (1996) and Gupta (1996) use measures on the average banks' balance sheet or income statement to derive an overall assessment on financial stability. All of these approaches have in common that the final classification of a systemic crisis is a binary choice, even though most decision variables are expressed as metric ratios. A different approach is presented by Laeven and Valencia (2010, 2011): The authors use the actual extent of government intervention measures, normalized as percent of the gross domestic product, to assign different degrees of systemic crises.

3.3. Achieving Stability in the Financial Sector

This section discusses different measures that help achieving and keeping financial stability. The measures presented in this section aim at the preventive provision of financial stability. Measures for the restoration of financial stability during a crisis

[1] As will be discussed in the project on the "Liquidity Dynamics of Bank Defaults", the USA for example has a quite extensive history of bank defaults.

follow in the subsequent section. In general, there is a wide variety of instruments that regulatory authorities, governments, and central banks may use to keep the financial sector stable: Governments and regulation have the lender of last resort, deposit insurance, minimum solvency and liquidity requirements as well as general monitoring activities at hand. Central banks are able to influence financial stability with their decisions on monetary policy.

3.3.1. Regulation – Lender of Last Resort

The idea of a lender of last resort dates back to 1873 when Walter Bagehot formulated its doctrine in response to an illiquidity-induced banking crisis in England. Following his postulation, a central bank should provide liquidity assistance to banks under three conditions: First, central banks should provide liquidity only to illiquid institutions. The failure of insolvent banks, on the contrary, is a necessary process to screen out inefficient institutions. In addition, to make sure that central banks extend loans to solvent banks only, Bagehot suggests that liquidity should only be provided against good collateral. Second, central banks should only provide liquidity as an emergency assistance. Loans from the central bank should be costly and charge penalizing interest rates, so that banks only use these facilities if all other options are depleted. Third, central banks should announce their willingness to lend without limits to any institution that requires liquidity assistance. As long as the markets assess this statement to be credible, any contagion risk from illiquidity within the financial sector should be low.

There are, however, some practical problems with the concept of the lender of last resort in modern economies. Following the "Too-Big-To-Fail" discussion, central banks with the proclaimed goal of sustaining a stable financial sector might be inclined to provide liquidity assistance to insolvent banks if they assess their systemic importance to be high. While this might help keeping the market stable in the short run, it clearly contradicts the first of Bagehot's conditions. However, not only central banks might feel the pressure to save insolvent institutions, political processes might also induce the bailout of otherwise insolvent banks (Rochet 2008).

3.3.2. Regulation – Deposit Insurance

The second regulatory measure that aims at securing the liquidity of banking institutions is deposit insurance. Deposit insurance intends to prevent bank runs and protect small and unsophisticated depositors from losses resulting from bank failure. Deposit insurance schemes can be characterized in several dimensions. Table 3-1: gives a short overview on the most relevant factors:

Table 3-1: Differences in Deposit Insurance Schemes

Dimension	Options	Description
Formalization	Explicit Implicit	Deposit insurance may either be explicit or implicit. Implicit deposit insurance relies on the assumption of the market that the regulatory authorities or the government will repay depositors in the case of a bank failure. Implicit deposit insurance schemes are not legally binding and, by design, unclear about extent and the deposits covered. Explicit deposit insurance, on the contrary, formalizes its commitment in a legally binding form.
Funding	Ex-Post Ex-Ante	Ex-post funding of deposit insurance triggers the transfer of funds from the remaining banking institutions to the depositors of a failed bank in the amount equivalent to the deposits insured. Ex-ante financing, on the contrary, requires participating banks to pay an insurance premium. These premiums are accumulated in the deposit insurance fund and paid out to depositors of a failed institution.
Premiums	Flat Size Deposits Risk-Based	From a theoretical point-of-view, deposit insurance premiums should be calculated based on the risk a bank poses to the insurance scheme. Bank risk, however, is a very vague concept and there is hardly a consensus on how to measure risk of banks appropriately. There are several different and more practical approaches in place for the calculation of deposit insurance premiums. The most basic approach collects payments evenly from all participating institutions. More sophisticated approaches use different measures of bank size or the insured deposits to assess each bank's required payments.
Co-Insurance	Yes No	Co-insurance refers to the depositors' contribution to the deposit insurance scheme. Under co-insurance, each depositor will only receive some, typically high, fraction of its original deposits. Co-insurance keeps some part of the monitoring incentive for depositors in place. As a drawback, with co-insurance bank-runs might still be a possible equilibrium among depositors
Eligible Deposits	Assets Limits	The goal of deposit insurance is to protect small and unsophisticated depositors. Deposits eligible for insurance are typically restricted to simple financial instruments like savings and checking accounts. Additionally, insurance schemes usually restrict the maximum amount that each depositor receives in case of a failure.
Membership	Optional Mandatory	Membership in the deposit insurance scheme may either be optional or mandatory. There are also several insurance schemes in place that combine a mandatory basic protection with an optional extended protection.

Source: Bernet and Walter (2009)

There are several additional dimensions that need to be considered in the actual design of a deposit insurance scheme. From an academic perspective, these are, however, of lesser interest, i.e. legal form of the fund, governance, and administration of the fund.

3.3.3. Regulation – Liquidity and Capital Adequacy

A highly debated issue of the regulatory measures are minimum solvency, and very recently, minimum liquidity requirements. On an international scale, Basel I and Basel II are the most prominent banking regulation frameworks. Both are designed as solvency regulations (i.e. minimum equity ratios relative to risk-weighted assets). The rationale behind solvency regulations is twofold: First, minimum equity requirements are supposed to provide a cushion against losses and, hence, decrease the probability of failure for each individual bank. Second, minimum equity requirements increase the stake of each shareholder in a bank. The higher exposure of the shareholder also increases the potential loss in the case of a default. Shareholders should therefore have stronger incentives to properly monitor their managers and make sure that the risk of the bank is limited to an appropriate amount (Rochet 2008). With Basel I and Basel II as solvency regulations, the most recent developments in the Basel III framework extend the concept of minimum requirements to two liquidity ratios. These minimum liquidity requirements are a direct response to the apparently too low liquidity cushions of banks during the subprime crisis.

3.3.4. Regulation – Monitoring

An often neglected aspect of regulation is the on-going monitoring of financial intermediaries. Even though this concept is relatively vague, one of the three pillars that form the Basel II-framework is wholly dedicated to the monitoring of banking institutions. The monitoring requirement forces the regulatory institutions to constantly oversee and assess the bank-internal risk controlling processes. It is hence not only a tool that allows identifying excessive risk within a particular banking institutions at an early stage, but also to gain insight in industry-wide developments that might potentially threaten the stability in the financial system.

3.3.5. Monetary Policy

The primary goal of monetary policy is price stability. Historically, most central banks were founded only to keep inflation levels in the designated areas (Goodhart 1988). Price stability entails the prevention of high levels of inflation, but also the prevention of very low levels of inflation or even deflation. High and more importantly unexpected inflation, resulting in the devaluation of loans in real terms, leads to the redistribution of wealth from lenders to borrowers. Extremely low inflation rates, and hence low nominal interest rates, increase average cash holdings leading to inefficient intermediation levels for the financial sector (Garcia-Herrero and Rio Lopez 2012).

There is an on-going debate whether price stability should be the sole goal of central banks and whether price stability and financial stability are complementary or conflicting goals. Advocates of the theory that central banks should only focus on price stability argue that this commitment makes the course of actions of the central banks more predictable and markets can then target the remaining problems more efficiently. Without the clear focus on price stability, market participants are not able to predict the central banks' actions accurately and are then forced to act in an uncoordinated and inefficient manner (Leijonhufvod 2007). Further support for the focus on price stability alone comes from Honohan and Klingebiel (2000). In their empirical study, they find that the support of liquidity prior to financial crises in an attempt to foster the economic activity is usually merely a way to delay the recognition of a crisis. According to their study, this provision of liquidity is also the most significant predictor for ex-post high fiscal cost of a crisis. While theory and evidence suggest that the central banks' focus should lie on price stability, most central banks considerably neglected most of their inflation concerns during the subprime and the sovereign-debt crisis for the sake of fostering economic activity.

In line with this observation, there is literature supporting the view that price stability and financial stability are complementary goals. Supporting this hypothesis, Schwartz (1995) argues that predictable price levels lead to predictable interest rate levels. Assuming responsible behaviour of financial intermediaries, predictable interest rates minimize the risk of unintended interest rate mismatches. Predictable interest rates should further lower the inflation risk premium for long-term interest rates. Similarly, Padoa-Schioppa (2002) and Issing (2003) argue that price stability is a necessary requirement for the stability of the financial sector, but not a sufficient one.

Contrary to these findings, there are also studies that find a conflicting relation between price and financial stability. Mishkin (1996), for example, argues that an increase in interest rates that is necessary to keep inflation low, might negatively affect the banks' balance sheets. Capital inflows associated with high interest attract foreign funds, leading to over-borrowing and hence induce overall increases in credit risk. Similarly, Cukierman (1992) argues that the goal of keeping inflation low might force central banks to substantially increase interest rates over short periods of time. Banks, in turn, are not able to pass changes in interest rate levels to most of their assets or liabilities, leading to a larger interest mismatches on the banks' balance sheets increasing overall market risk. In addition, as Fisher (1933) pointed out a long time ago, too low inflation rates might also induce financial instability. Fisher argues that low interest rates – or even more so deflation – reduce the profit margin of the traditional banking model that employs term transformation. Deflation additionally increases the incentive for strategic default on a loan, increasing credit risk for the financial intermediaries.

3.3.6. Competition

In addition to regulation and monetary policy, a strongly debated factor that contributes to the stability of a financial sector is the competition within that sector. Depending on the point-of-view, theoretical considerations arrive at opposing conclusions regarding the impact of competition on the financial stability. Taking the perspective of the financial intermediaries, a more concentrated financial market should, on average, yield higher profits through monopoly rents to banking institutions. Higher profits, in turn, should allow banks to build up equity cushions against unexpected shocks. On a theoretical basis this view is supported by studies of Marcus (1984), Chan et al. (1986), and Keeley (1990). Empirical results arriving at same conclusion come from Demirguc-Kunt and Detragiache (2002), Beck et al. (2006), and Evrensel (2008). Their analyses show that countries with more concentrated banking systems are less likely to experience systemic crises. In addition, Chang et al. (2008) find that more concentrated banking systems show lower rates of non-performing loans.

Taking the viewpoint of the borrowers, the concentration-fragility hypothesis, theoretically formalized in Boyd and De Nicolo (2005), claims that higher market power should allow banks to charge higher interest rates. Faced with higher interest rates on their projects, borrowers have an incentive to take excessive amounts of risk, resulting in the destabilization of the financial sector. In an empirical study, Keeley (1990) finds that higher competition did in fact erode charter values of banks in the USA resulting in higher overall fragility. Dick (2006) finds that loan losses increased following the deregulation of the US-financial sector in the 1990s. Measuring bank riskiness more directly, Boyd, De Nicolo, and Jalal (2006) and Uhde and Heimeshoff (2009) use the z-score to find that banks tend to be closer to default in more competitive banking systems. Additionally, Rajan (2010) ties the recent financial crisis to the competition-fragility hypothesis. Deregulation, by increasing competition, and securitization, by enabling market participants to shift credit risk more effectively, provided both, the incentives and the tools to take on more complex forms of risk than ever before.

Building on the inconclusive theoretical as well as empirical predictions of the impact of competition on stability in the financial sector, additional studies in fact do not find a significant impact of concentration on financial stability (Ruiz-Porras 2007; Jimenez, Lopez, and Saurina 2007). Further supporting this view, a very recent study finds that the effects of concentration on stability vary between high and low income countries. Additionally, the authors find that there are channel effects for both, the stability and the fragility hypothesis. However, there is no direct impact of competition on the stability or fragility of the financial sector and the net impact of the channel effects are inconclusive (Bretschger et al. 2012). On a conceptual level, it is important to note that competition is not a well-defined concept, which might at least partly contribute to the controversial results in empirical studies (Matutes and Vives 2000; Demirguc-Kunt et al. 2004; Beck 2008).

3.4. Restoring Stability in the Financial Sector

If regulation and / or monetary policy fail to achieve a stable financial sector, governments, regulatory authorities, and central banks have several more measures at their disposal that aim at restoring financial stability during and after a crisis. During a crisis, the goal is to restore public confidence in the financial sector and hence to minimize the costs associated with the crisis. This period is also called the containment phase. After the crisis, during the resolution phase, the goal is to restore the efficient functionality of the financial system as well as to strengthen the banks' balance sheets. Just as the respective goals differ for containment and resolution phase, so do the measures at disposal (Laeven and Valencia 2008).

Measures for the containment of a banking crisis include the suspension of convertibility of deposits, regulatory capital forbearance, liquidity support, and governmental guarantees. Suspension of convertibility of deposits, for example through bank holidays, is an emergency measure that prevents depositors from converting their deposits into cash. Banking crises, especially if triggered by the lack of trust in the financial sector, are often amplified by increasing withdrawals from depositors. This outflow of cheap refinancing then increases the liquidity needs of banking institutions. The suspension of convertibility of deposits hence aims at buying time for banks to restore appropriate capitalization and liquidity levels and regain the depositors' trust. Similarly, emergency liquidity support and government guarantees both intend to improve the public perception of the banking institutions' soundness. If depositors' trust in the liquidity of banks is undermined, additional capital in the form of emergency liquidity support, or the intent to provide additional capital, in the form of government guarantees, are able to mitigate these concerns. During the containment phase, the restoration of depositors' trust in the financial system is important to prevent the fragility of single institutions to spill-over to the whole sector (Laeven and Valencia 2008).

During the resolution phase, the major goal is the actual financial and / or operational restructuring of financial institutions. The available tools in this phase include assisted workouts of distressed loans, debt forgiveness, establishing government-owned management companies, and recapitalizations. The government usually grants loan subsidies for the assisted workout of distressed loans or general government-assisted recapitalization only if current shareholders also inject additional capital. Under this condition, markets should only supply banks with additional capital if they lack liquidity rather than solvency. Debt forgiveness, also in generalized forms such as inflation or currency depreciation, on the contrary, bear a strong risk for moral hazard as even liquid debtors might stop their repayments in the hope of becoming a beneficiary of the debt relief program. On the upside, inflation at least used to be an affordable measure for governments in any state of a crisis as opposed to other tools that are associated with more direct costs to the public. Government-owned asset management companies, often also termed “bad banks”, are a special form of debt relief programs. In contrast to debt relief in the form of inflation, the asset management companies specifically target only assets in the banking portfolios that might potentially lead to large losses. Governments allow banks to remove these assets from their balance sheets, reducing the market’s uncertainty about future losses. As the government usually assumes at least a part of the banks’ losses, this kind of debt relief program, might not only be perceived as unfair, it also induces excessive risk taking in the future if markets assume that future crises might lead to similar relief programs (Laeven and Valencia 2008). Also, evidence on the effectiveness of government-owned asset management companies which are designed to buy and resolve distressed loans is mixed. Klingebiel (2000) shows that bad banks work better for crises that are triggered by real estate markets. In crises that are triggered by loans to large firms are, on the contrary, bad banks are of little use.

3.5. Why Should the Financial Sector be Stable?

In this last section of the general framework on financial stability, after defining stability of the financial sector, ways to measure it and measures for achieving or restoring it, this section provides a short overview of the most fundamental question related to this topic: Why should the financial sector be stable? In a nutshell, the stability of the financial sector is important because the costs associated with instability are extremely high. Leaving potential spill-over effects to other industries aside, fragility of financial institutions affects shareholders, depositors, other creditors, borrowers, and finally taxpayers (Hoggarth et al. 2002). Shareholders directly suffer from any losses of a bank’s market value. This aspect, however, is not very different from any other equity investment and therefore not a major concern to anyone else than the shareholder itself. Depositors are affected by bank fragility through the potential loss of their deposits. As already outlined, however, this risk can be mitigated by the introduction of deposit insurance schemes. Lenders other than depositors are affected by bank failures as they are explicitly excluded from most deposit insurance schemes. The threat of potential loss for these supposedly more sophisticated creditors is important to keep the screening and monitoring incentives for these groups high. Borrowers of a bank are affected by the default of the institution, as their uncertainty about the current and future funding conditions sharply increases with the uncertainty about the soundness of their current bank.

Costs to these stakeholders might be significant. When talking about the costs of financial crises, the major focus, however, lies on costs to taxpayers and the economy as a whole. There are two major problems when assessing these costs to an economy: First, banking crises typically arise during recessions. This leads to problems in identifying to what extent output loss and public expenditures are triggered by the financial crisis and to what extent by the negative effects of the on-going recession (Hoggarth et al. 2002). Additionally, there can be endogeneity issues in assessing to what extent exogenous shocks that triggered a banking crisis also caused a decline in overall output (Dell'Ariccia et al. 2008). While researchers have come up with various ways that try to disentangle these effects, it is clear that banking crises tend to spill-over to the economy by decelerating credit to the private sector, the so-called credit crunch, which in turn slows down economic growth (Kaminsky and Reinhart 1999; Demirguc-Kunt et al. 2006).

Literature typically distinguishes between two different costs to the public that are caused by financial crises: Direct resolution costs to the government and broader costs to the welfare of the economy as a whole. Resolution costs include, for example, the bail-out of financial intermediaries. Costs to the welfare of the economy are commonly measured as the decrease in gross domestic product (GDP). Hoggarth et al. (2002) present a comprehensive summary of the collections of costs for financial crises based on studies by Barth et al. 2000, Caprio and Klingebiel 1999, and the IMF 1999. Analysing a total of 24 major banking crises, they find fiscal costs that average 16% of the annual GDP. This value increases to an average of 23% when focusing on twin crises, i.e. banking crises that are accompanied by a currency crisis. For sole banking crises, the average cost is distinctively lower at 5% of GDP. Kaminsky and Reinhart (1999) find similar values of average bail-out costs amounting to 13% of GDP for twin crises and 5% for singular banking crises. In this context, however, it is important to note that the causal relationship between banking and currency crises is all but clear. Emerging economies, on average, suffer distinctively more from banking crises with an average resolution cost of 17.5% as opposed to 12% for developed countries.

Costs to the welfare of an economy, measured by the losses in output also heavily depend on whether an economy deals with a banking crisis alone or with a twin crisis. Using similar methodologies but different samples, IMF (1998), Bordo et al. (2001), and Hoggarth et al. (2002) find that sole banking crises range around 6-8% of GDP in output losses. For twin crises, the estimations increase to 15%, 16%, and 23% of GDP, respectively. Only Hutchinson and Noy (2005), focusing on a four year horizon, find relatively moderate levels totalling in 5-10% of output losses.

Summarizing these findings, it is safe to say that assessing the exact costs of a financial crisis is a quite inaccurate task. It is also clear, however, that costs are very significant. In the next four chapters, I present four different studies that help gaining a better understanding of how to circumvent or reduce these costs in the future.

4. *Information or Insurance – On the Role of Loan Officer Discretion in Credit Assessment*

Martin Brown*, Matthias Schaller**, Simone Westerfeld***, Markus Heusler****

Abstract

We employ a unique dataset of credit assessments for 3,756 small businesses by nine banks using an identical rating model to examine (i) to what extent loan officers use their discretion to smooth credit ratings of their clients, and (ii) to assess whether this use of discretion is driven by information about the creditworthiness of the borrower or by the insurance of clients against fluctuations in lending conditions. Our results show that loan officers make extensive use of their discretion to smooth clients' credit ratings: One in five rating shocks induced by changes in the quantitative assessment of a client is reversed by the loan officer, independent of whether the borrower experiences a positive or a negative rating shock. We find that this smoothing of credit ratings is hardly driven by soft information: Loan officers are just as likely to smooth persistent and market-related shocks as they are to smooth temporary and firm-specific shocks. We do find that loan officers are more likely to smooth ratings at banks where interest rates are more risk-sensitive. However, this behavior is not purely driven by an implicit insurance contract between loan officers and their clients. Instead, the use of discretion by loan officers seems at least partly driven by their reluctance to communicate price changes: Within banks loan officers are not more likely to smooth rating changes which lead to the strongest interest rate changes.

Keywords: Relationship banking, Asymmetric information, Implicit contracts, Credit rating

JEL classification numbers: G21, L14, D82

---

* University of St. Gallen (e-mail: martin.brown@unisg.ch), ** University of St. Gallen (e-mail: matthias.schaller@unisg.ch), *** University of Applied Sciences Northwestern Switzerland (e-mail: simone.westerfeld@fhnw.ch), **** Risk Solution Network AG (e-mail: markus.heusler@rsnag.ch).

Acknowledgements: We thank Tobias Berg, Hans Degryse, Emilia Garcia-Appendini, Charles Kahn, Steven Ongena, George Pennacchi, Christian Schmid, Greg Udell, Alberto Zazzaro, participants at the International Doctoral Seminar for Banking and Finance in Liechtenstein, the MOFIR Conference in Ancona, and the Münster Workshop on Banking as well as seminar participants at the University of St. Gallen and the University of Fribourg for helpful suggestions. We thank Jochen Maurer and Marcus Kahler for their assistance in preparing the data.

4.1.Introduction

The theory of financial intermediation suggests that one key function of relationship banking is to overcome informational asymmetries between the lender and the borrower. Repeated interaction enables lenders to produce information about the creditworthiness of borrowers (Sharpe 1990, Petersen and Rajan 1994) and mitigates moral hazard by providing dynamic incentives for borrowers to choose safe projects, provide effort and repay loans (see e.g. Stiglitz and Weiss 1983).[2] This “information view” of relationship banking provides a strong rationale for the widely observed discretion of loan officers in credit assessments. The incorporation of “soft” information on a client’s creditworthiness in the credit assessment requires a rating process in which loan officers can complement quantitative assessments of financial statement data with qualitative information about the client’s creditworthiness, e.g. through the use of hybrid rating models.

The theory of implicit contracts (Fried and Howitt 1980)[3] provides an alternative explanation for the existence of long-term credit relationships: Repeated interaction may enable (risk-neutral) lenders to insure their (risk-averse) borrowers against fluctuations in lending conditions. This “insurance” view of relationship banking also provides a rationale for giving loan officers discretion in credit assessments: If credit assessments were purely based on quantitative indicators, fluctuations in aggregate economic conditions could trigger, e.g. through covenant breaches, sudden changes in the available loan volume, the interest rates or other non-price loan terms (e.g. maturity, collateral).

In this paper, we employ a unique dataset on credit assessments of small businesses to examine (i) to what extent loan officers use their discretion for smoothing shocks to credit ratings of their clients and (ii) to assess whether the use of discretion by loan officers is primarily driven by soft information about the actual creditworthiness of the client or by the loan officers’ effort to insure their customers against shocks to their

[2] A drawback to repeated interaction, i.e. “hold-up” of borrowers, is developed in the theories of e.g. Sharpe (1990) and Von Thadden (2004). Recent empirical evidence by Ioannidou and Ongena (2010) suggests that banks do, in fact, hold-up their borrowers in long-term lending relationships.

[3] The theory of implicit contracts was originally formulated in the context of the labor market in Bailey (1974) and Azariadis (1975).

lending terms. Our analysis is based on credit assessments for 3,756 small businesses by nine Swiss banks over the period 2006-2011. All of these banks employ an identical hybrid credit rating tool: A quantitative assessment of financial statement data is complemented by a qualitative assessment of the firm and its industry. In addition, loan officers at all banks have the discretion to override calculated credit ratings.

Our dataset allows us to analyze how loan officers react to shocks in the objective creditworthiness of their clients: Do loan officers make use of qualitative assessments and rating overrides to "smooth" changes to the credit ratings of their clients over time? Our data also allows analyzing the driving forces behind loan officer behavior. First, we test the information content of discretionary rating changes, i.e. to what extent rating changes induced by loan officers predict subsequent changes in the observable creditworthiness of customers. Second, exploiting differences in lending processes across banks, we study whether discretionary rating changes are driven by insurance considerations. Are loan officers more likely to smooth credit ratings when the bank explicitly links credit ratings to lending terms?

Our analysis yields three main results: First, loan officers make extensive use of their discretion to smooth clients' credit ratings. Roughly one in five rating changes which would be induced by changes in financial statement data of borrowers is smoothed out by loan officers. Smoothing of credit ratings is prevalent across all rating classes and is independent of whether the borrower experiences a negative rating shock (weaker financial statement data) or a positive rating shock (stronger financial statement data) to their rating. Second, the smoothing of credit ratings by loan officers is not related to firm-specific soft information about the future creditworthiness of borrowers. While many rating shocks are only temporary, loan officers seem unable to identify these temporary shocks and hence to limit their smoothing on such instances. Furthermore, loan officers show similar smoothing behavior for market-related and firm-specific shocks. Third, the smoothing of credit ratings is compatible with the insurance view of credit relationships: Loan offers are much more likely to smooth ratings at banks with risk-sensitive interest rates than at banks which do not practice risk-adjusted pricing. However, it would be false to interpret the stronger smoothing of price-relevant rating shocks as the outcome of an implicit contract between loan officers and their clients. Within banks, loan officers are not more likely to smooth rating shocks which lead to stronger interest rate changes. The results suggest that what looks like an implicit insurance contract is rather the result of the loan officers' reluctance to communicate interest rate changes to their clients.

Overall, our results challenge the dominating "information" view of credit relationships in the financial intermediation literature. The widespread use of discretion by loan officers seems not only motivated by the objective of yielding more accurate assessments of the creditworthiness of borrowers. Loan officer discretion also plays a key role as banks insure their clients against changes in lending terms.

Our findings contribute to the empirical literature on insurance provision in long-term bank relations, i.e. implicit contracting. Berger and Udell (1992) and Berlin and Mester (1998, 1999) provide evidence that banks smooth loan rates to their clients in response to interest rate shocks and shocks to the aggregate credit risk. Petersen and Rajan (1995) show that banks smooth loan rates in response to changes in the firm-level credit risk. Elsas and Krahnen (1998) provide evidence that "Hausbank" relationships result in the provision of liquidity insurance to borrowers. However, as argued by Berlin and Mester (1998), the insensitivity of lending terms to interest rate shocks and firm-level credit risk may be driven by inefficient bank processes rather than risk-sharing. Our study mitigates this concern by providing direct evidence for active "smoothing" of credit ratings by loan officers and linking this smoothing to the potential interest rate implications of rating changes.

We contribute to the recent literature on the use of "soft" versus "hard" information in bank lending and the role of loan officers in producing soft information.[4] Based on credit file data from four German banks, Grunert et al. (2005) provide evidence that the combined use of "hard" quantitative information and "soft" qualitative information leads to a more accurate prediction of future default events for medium-sized corporate clients. Scott (2006) provides evidence supporting the conjecture that loan officers play a key role in producing soft information within banks. Using survey evidence, he

[4] Several earlier studies suggest that relationship lending is particularly valuable to opaque, i.e. small and young, firms by providing better access to credit at more favorable price and non-price terms (e.g. Berger and Udell 1995, Cole 1998, Harhoff and Körting 1998, Degryse and Van Cayseele 2000). However, these studies do not directly document the use of soft information in credit relationships.

shows that loan officer turnover has a negative effect on the availability of credit to small US firms. Uchida et al. (2012) use survey data on Japanese firms to document that loan officer activity positively affects the soft information a bank produces on its small business clients. Using credit file data of a multinational bank in Argentina, Degryse et al. (2011) show that loan officers use their discretion in relationship lending for the incorporation of non-contractible soft information into the lending decision. They show that the soft information gathered by loan officers affects the credit limit set for small business clients. Cerquiero et al. (2011) provide evidence suggesting that soft information has a significant effect on lending terms to small US firms. They document a substantial degree of dispersion in lending terms to observably identical businesses and show that this variation in loan terms is stronger for small and young firms. Confirming these findings, Qian et al. (2010) find that internal "soft" information of a large Chinese bank has a more pronounced effect on price and non-price terms of loan contracts than public "hard" information. Our findings complement this literature by showing that information may not always be the primary driver of discretion in (small) business lending. We show that changes in the subjective assessment of clients over the course of existing relationships may be hardly related to firm-specific soft information at all.

Finally, we contribute to the literature on how the organizational structure and incentives within banks impact the behavior of loan officers. Stein (2002) suggests that hierarchical structures of banks, i.e. centralized as opposed to decentralized loan approvals may limit the production of soft information within banks. In line with this prediction, evidence by Berger et al. (2005) and Uchida et al. (2011) suggests that loan officers produce more soft information about their clients in small banks as compared to large banks. Liberti and Mian (2009) show that subjective information is used less frequently in lending processes if the hierarchical / geographical distance between the loan officer and the approver is large. Agarwal and Hauswald (2010a) show that the geographical distance between a bank and its clients affects the collection of relation-specific information, while Agarwal and Hauswald (2010b) show that bank branches with a more delegated authority in lending are more prone to collect such information. Hertzberg et al. (2010) examine the impact of anticipated loan officer rotation on the use of information in the lending process. They find that anticipated control leads to a more conservative assessment of clients. Finally, Berg et al. (2012) find strong evidence for the loan officers' manipulation of credit applications, even though there setting is restricted to a purely quantitative rating model. Their analyses suggest that loan officers actively alter hard information on customers during the application process to improve the rating result and lower the rejection rates of their clients. Our findings complement the above literature by documenting how the pricing policies of banks impact the way loan officers use their discretionary power in the credit assessment process. Our results suggest that when lending terms are sensitive to credit ratings, loan officers are more likely to use this discretion to smooth credit assessments and thus loan terms.

The rest of the paper is organized as follows: Section 2 describes our data. Section 3 documents the smoothing of credit ratings in our dataset. Section 4 and 5 examine to what extent the observed smoothing of credit ratings is driven by information or insurance considerations. Section 6 concludes.

4.2. Data

Our dataset covers all credit assessments for small business clients conducted by nine Swiss banks during the period 2006 to 2011. Each bank in the sample is a regionally focused commercial bank. Measured by total assets, the size of the banks in our sample varies from roughly 3 to 39 Billion Swiss Francs.[5] Mortgage lending to households and small business lending are the major business lines for each bank. Small businesses are defined as corporate customers with an annual turnover of up to 10 million Swiss Francs. For clients in this segment, all nine banks employ a common credit rating tool which was developed and is currently serviced by an external service provider.

Table 4-1 provides a definition of all variables employed in our analysis. Table 4-2 provides summary statistics for these variables. Table 4-3 provides an overview of the available observations per bank. Our dataset contains information on 14,974 credit assessments for 6,934 firms. As shown by Table 4-3 the number of observations differs considerably across banks due to differences in bank size, but also due to the fact that not all banks introduced the rating tool at the same time. Four banks (labeled

[5] For the period 2006 to 2011, 1CHF ranged between 0.75 USD and 1.30 USD.

Bank B, C, D, E respectively) introduced the rating tool in 2006, one bank in 2007 (Bank A), three banks in 2008 (Banks G, H, I) and one bank in 2009 (Bank F).

Table 4-1: Definition of Variables

This table provides definitions for all variables used throughout our empirical analyses.

	Definition
Discretion	Proposed rating minus the hypothetical rating based on the current quantitative assessment and the previous qualitative assessment of a customer.
Rating Shock	The hypothetical credit rating of a client using its current quantitative and previous qualitative assessment minus his/her previous rating.
Negative Shock	Dummy variable which is 1 if *Rating Shock* ≤ 0, and 0 otherwise.
Positive Shock	Dummy variable which is 1 if *Rating Shock* ≥ 0, and 0 otherwise.
Quantitative Shock	Difference between the current quantitative score and the quantitative score of the previous rating application.
Calculated $Rating_{t-1}$	Rating calculated in the previous credit assessment of this customer. Rating classes range from 1: worst to 8: best.
Industry	Dummy variables, coding the industry into one of 21 industries.
Size	Natural logarithm of the balance sheet total (in Swiss Francs) of each customer.
Temporary	Dummy variable which is 1 if the *Rating Shock* in t+1 - assuming constant qualitative scores in t-1, t, and t+1 - has a different sign than the *Rating Shock* in t. Observations with no *Rating Shock* in t have no value for this variable.
Good Market Conditions	Dummy variable taking the value one if observations are in an IndustryYear that has a high share (top quartile) of positive *Rating Shocks*.
Bad Market Conditions	Dummy variable taking the value one if observations are in an IndustryYear that has a high share (top quartile) of negative *Rating Shocks*.
Experience Loan Officer	Dummy variable, coding the experience of each loan officer measured as the number of previous loan applications (0: less than 50, 1: more than 50).
Experience Bank	Dummy variable, coding the experience of each bank with the rating tool measured as the time since the introduction of the rating tool at the bank (0: less than 24 months, 1: more than 24 months).
No Influence	Dummy variable indicating that proposed rating classes have no impact on interest rates within a bank. (0: no, 1: yes).
Risk-adjusted Pricing	Dummy variable indicating whether the bank has an explicit rule relating rating classes to interest rates, but the bank does not use the pricing tool offered by the external rating provider (0: no, 1: yes).
Pricing Tool	Dummy variable indicating that the bank uses the pricing tool offered by the external rating provider (0: no, 1: yes).

Table 4-2: Summary Statistics

The table shows the summary statistics of the variables employed in our empirical analysis. The summary statistics include the number of observations available, the mean values and standard deviations, as well as the minimum and maximum values. See Table 4-1 for a detailed definition of all variables.

	Obs.	Mean	Std. Dev.	Min	Max
Discretion	3,756	0.04	0.76	-5	7
Rating Shock	3,756	-0.02	1.44	-7	7
Calculated Rating$_{t-1}$	3,756	4.83	1.95	1	8
Size	3,756	8.86	0.19	7.78	9.67
Temporary	1,027	0.46	0.50	0	1
Good Market Conditions	3,756	0.26	0.44	0	1
Bad Market Conditions	3,756	0.25	0.43	0	1
High Experience Loan Officer	1,027	0.44	0.50	0	1
High Experience Bank	1,027	0.38	0.49	0	1
No Influence	3,756	0.10	0.30	0	1
Risk-adjusted Pricing	3,756	0.37	0.48	0	1
Pricing Tool	3,756	0.53	0.50	0	1

Table 4-3: Observations by Bank

The table presents the number of rating applications across banks. Banks are labeled with consecutive letters A to I. Column (1) reports the total number of available observations in our data sample. Column (2) reports the number of observations that we actually employ in our analysis. We only use second observations of each customer in our data sample, as we focus our analyses on changes in rating data and want to prevent distorions due to previous shocks. Column (3) reports the relative share of each bank in our total sample, as based on actual values in the analyses. Column (4) reports the pricing regime of each bank, i.e. how sensitive interest rates are to credit ratings. See Table 4-1 for a detailed definition of all variables.

	(1)	(2)	(3)	(4)
Bank	Total Observations in Dataset	Observations Employed in Analysis	Share	Pricing regime
A	613	179	4.8%	Risk-adjusted pricing
B	493	135	3.6%	Risk-adjusted pricing
C	2,471	591	15.7%	Pricing tool
D	1,402	369	9.8%	No influence
E	5,319	1,392	37.1%	Pricing tool
F	1,778	291	7.7%	Risk-adjusted pricing
G	112	20	0.5%	Pricing tool
H	2,296	676	18.0%	Risk-adjusted pricing
I	490	103	2.7%	Risk-adjusted pricing
Total	14,974	3,756	100%	

4.3. The Credit Rating Process

All banks in our sample employ the same hybrid credit rating process: The calculated rating class for a client depends on quantitative information as well as qualitative information. Loan officers can influence the calculated rating of a borrower through their qualitative assessment of the client. In addition, loan officers at all banks have the opportunity to override calculated ratings, i.e. to propose a rating class which differs from the one calculated by the rating model.

In the first step of a credit assessment, quantitative information based on seven financial ratios from the financial statement, plus past default behavior and firm age are aggregated to a quantitative score. The quantitative score ranges from zero (lowest score - highest probability of default) to one (highest score - lowest probability of default).

In a second step, the loan officer provides a qualitative assessment of the firm and the industry in which the firm is active. This assessment is based on seven indicators each of which the loan officer grades on an ordinal scale, i.e. “bad”, “average”, “good”. The scores on the seven questions are transformed to an overall qualitative score that ranges from zero (worst score - highest probability of default) to one (best score - lowest probability of default).

The quantitative score and the qualitative score are then weighted and transformed to a calculated rating on a scale of 1 (worst rating - highest probability of default) to 8 (best rating - lowest probability of default). For quantitative scores lower than 0.75 the rating relies solely on quantitative information. For borrowers in this range the calculated rating results from a transformation of the continuous quantitative score to the discrete rating classes. For quantitative scores higher than 0.75 and lower than 0.875, the relative weight of the qualitative score increases monotonously with quantitative scores.[6] For quantitative scores higher than 0.875, the relative weight of the qualitative score remains constant. Appendix 4-I provides details about the rating process and the resulting rating classes depending on qualitative and quantitative assessment.

[6] The exact weighting of soft and hard information depends not only on the initial quantitative score, but also whether the qualitative score is above or below 0.5.

The loan officers in our sample do not know the rating model in detail, i.e. they are not instructed about the weighting of factors within the quantitative or qualitative scores or how these are transformed to the calculated rating classes. However, loan officers have the possibility to test different input parameters before the rating is actually saved and processed. This not only allows loan officers to adjust their qualitative assessment of a client iteratively. [7] It also allows them to derive the mechanics of the rating algorithm and their scope to influence ratings. Appendix 4-II provides a stylized illustration of the graphical user interface of the rating model.

At all banks, loan officers have the opportunity to override calculated ratings, i.e. to propose a rating class for a client which deviates from the calculated rating. Overrides may be done in either direction, i.e. upgrade or downgrade, and may encompass more than one rating step. If the loan officer decides to override a rating, he needs to state the underlying reasons for this decision. Permitted reasons include "existence of an alternative external rating", but also "bank-internal reasons" or "insufficient performance of the rating model".

Our data stems from the database of the external service provider of the rating tool and includes full information on all the input and output data of the tool for all credit assessments. For the assessment of a firm at time t, we observe the quantitative score obtained by the firm, the assessment of each qualitative indicator by the loan officer, as well as the resulting qualitative score. We further observe the calculated rating class as well as the rating class proposed by the loan officer.

4.4. Smoothing of Credit Ratings

4.4.1. Identification

In order to identify the smoothing of credit ratings by loan officers, we exploit the panel characteristics of our dataset: We analyze how qualitative assessments and rating

[7] Recent results by Berg et al. (2012) suggest that loan officers do in fact also manipulate quantitative information during loan applications. We are not able to test for manipulations of quantitative information. We argue, however, that the possibility to manipulate unobservable information - as is the case in our setting and not in the setting of Berg et al. (2012) - should minimize the incentive to actively alter quantitative information.

overrides by loan officers react to changes in the quantitative score of a given client. Underlying our analysis is a decomposition of changes in the credit rating for a client over time into two components: The first component *Rating Shock$_t$* measures the hypothetical rating change for the client based only on changes in his quantitative score. The second component *Discretion$_t$* measures the rating change induced by changes in the qualitative assessment and/or override by the loan officer.

$$\textit{Proposed Rating}_t - \textit{Calculated Rating}_{t-1} = \textit{Rating Shock}_t + \textit{Discretion}_t$$

whereby:

$$\textit{Rating Shock}_t = \textit{Calculated Rating}_{t,Qual(t-1)} - \textit{Calculated Rating}_{t-1}$$

$$\textit{Discretion}_t = \textit{Proposed Rating}_t - \textit{Calculated Rating}_{t,Qual(t-1)}$$

We calculate *Rating Shock$_t$* as the difference between a hypothetical rating based on the current quantitative assessment and the previous qualitative assessment of the client (*Calculated Rating$_{t,Qual(t-1)}$*) and the previously calculated rating of that same client (*Calculated Rating$_{t-1}$*). Thus the variable *Rating Shock* is positive or negative only if there is a rating-relevant increase or decline in the quantitative score of a client. As the quantitative score is a continuous function of the financial statement data, all borrowers experience changes in their quantitative score over time. We focus on the rating-relevant changes as we want to examine how loan officers react to changes in the quantitative score which may impact the lending terms for their clients. Changes in the quantitative score of a client from one credit assessment to another are, from the point of view of the loan officer, largely exogenous: These changes are driven only by changes in financial statement ratios as well as changes in repayment behavior of the client and are not related to any kind of assessment by the loan officer. The contribution of the loan officer to a rating change over time is captured by the variable *Discretion$_t$*. This variable measures the change in the rating which is the result of a change in the qualitative assessment between period t-1 and t and/or an override of the calculated rating by the loan officer in period t.

As illustrated by model [1], in the first part of our empirical analysis we relate the endogenous component of a rating change for firm i $Discretion_{i,t}$ to its exogenous component *Rating* $Shock_{i,t}$. At the firm-level, we include dummy variables for each initial rating class $\alpha_{PropRating,t-1}$ to control for heterogeneity in the level of credit risk. We further include industry dummies α_I to account for differences in the precision of the rating tool across industries. We control for the $Size_{i,t}$ of the firm (measured in ln CHF), as theory and existing evidence suggests that qualitative credit assessments by loan officers may be particularly important for small, financially more opaque firms. We control for unobserved heterogeneity in bank policies and economic conditions over time with bank*year fixed effects $\alpha_{B,t}$.[8]

In model [1] our key coefficient of interest is β_1 which measures the reaction of the loan officer in period t to an external *Rating Shock* for his or her client. We expect this coefficient to be negative if loan officers smooth credit ratings, i.e. use their *Discretion* to compensate shocks to the quantitative score.

$$[1]\ Discretion_{i,t} = \alpha_{PropRating_{t-1}} + \alpha_I + \alpha_{B,t} + \beta_1 \cdot Rating\ Shock_{i,t} + \beta_2 \cdot Size_{i,t} + \varepsilon_{i,t}$$

In order to estimate model [1] we employ information from 7,512 credit assessments for 3,756 different customers. For each customer we employ only the first and second credit assessment observed in our database. Thus *Rating* $Shock_t$ and $Discretion_t$ are calculated using the change in quantitative scores, qualitative scores and overrides between these two credit assessments. Hereby the time indicator t is the year in which we observed the second credit assessment of the client.

We restrict our analyses to these first two observations in order to avoid distorting effects as loan officers might be inclined to repeat any kind of discretionary exercise of influence in later rating applications. Also to minimize the influence of repeated use of

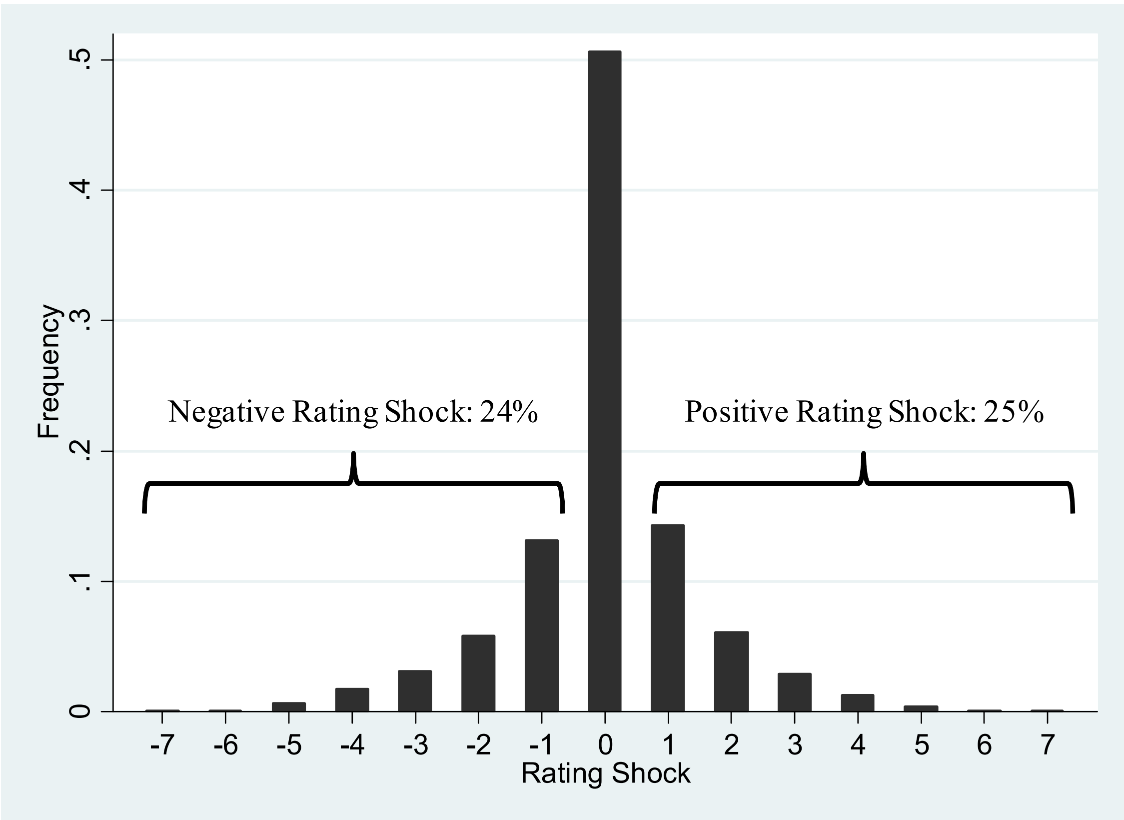
[8] As we observe the identity of the loan officer responsible for the customer (captured by a bank-specific ID number), in robustness tests we replace the bank*year fixed effects $\alpha_{B,t}$ in model [1] with loan officer*year fixed effects.

Discretion on our results we limit our analysis to those firms which did not experience a rating override at their first observed credit assessment.[9]

Figure 4-1: Exogenous and Discretionary rating changes

Panel A of Figure 4-1 presents the frequency distribution of *Rating Shock*. A negative *Rating Shock* indicates worsening objective information. Positive *Rating Shocks* indicate improved objective information. Panel B of Figure 4-1 shows the distribution of discretionary rating changes in response to *Rating Shocks*. Positive *Discretion* indicates an increase in the qualitative assessment and/or a positive override of the calculated rating. Negative *Discretion* indicates a reduction of the qualitative assessment and/or a negative override of the calculated rating. Sizes of bubbles indicate relative frequencies and sum to 100% across each value of *Rating Shock*.

Panel A: Distribution of Exogenous Rating Changes



[9] We exclude 1,368 observations in which loan officers had already made an override in the first observation. We further exclude five customers with missing information.

Panel B: Exogenous and Discretionary Rating Changes

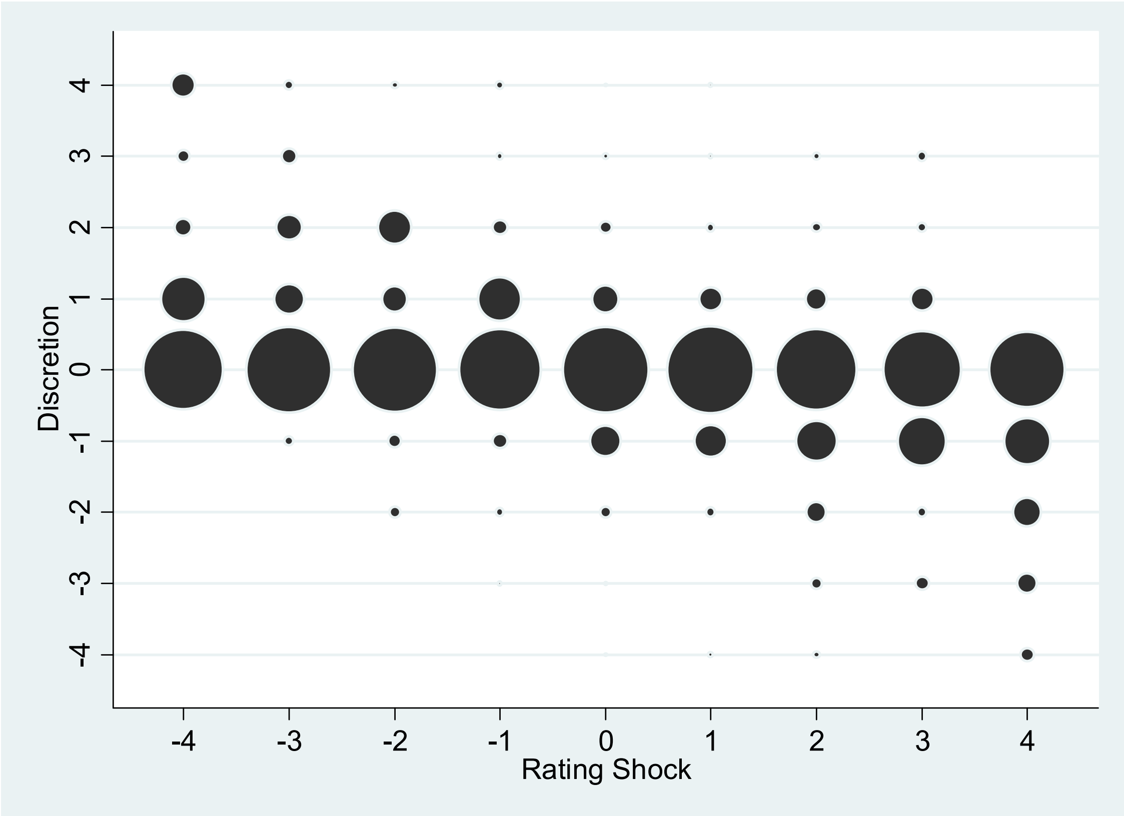


Figure 4-1A presents a histogram of the variable *Rating Shock*, i.e. the hypothetical rating changes which would have occurred to firms in our sample on the basis of changes in their quantitative score alone. For 24% of all observations in our sample we observe a decline in the quantitative score that would have triggered a downgrade in their credit rating. For 25% of our observations, the *Rating Shock* would have implied an upgrade of the clients' credit rating. The figure shows that for those clients who experienced a rating-relevant increase or decrease of their quantitative score, the most common rating change is by one or two notches. For 51% of the observations, the change in the quantitative score of the client was too small to trigger a shock to the client's credit rating.

Figure 4-1B illustrates how loan officers use their discretionary power to smooth *Rating Shocks*. The graph plots the variable *Discretion* on the vertical axis against the variable *Rating Shock* on the horizontal axis. The size of the bubbles in the graph reflects the frequency of observations conditioned on the value of *Rating Shock*, i.e. bubble sizes sum to one when added vertically. The figure displays a substantial degree of smoothing of credit ratings by loan officers. Loan officers improve the qualitative assessments and/or positively override calculated ratings of those customers whose rating would decline due to their quantitative score. They also lower the qualitative assessments and/or negatively override the calculated ratings of those customers whose rating would increase due to their quantitative score.

4.4.2. Baseline results

Table 4-4 presents our multivariate estimates of model [1] and confirms that loan officers make extensive use of their *Discretion* to smooth clients' credit ratings. All reported coefficients are based on linear regressions with standard errors clustered at the bank*year level and reported in brackets. Our baseline results are presented in Panel A. Column (1) presents full sample results including bank and year fixed effects, while column (2) includes interacted bank*year fixed effects and column (3) includes loan-officer*year fixed effects. In line with the picture presented in Figure 4-1, all three columns report a significant and economically relevant negative coefficient for *Rating Shock*. The estimates in columns (1-3) suggest that roughly 18% of rating changes which would be induced by changes in quantitative scores are reversed by loan officers. This result is robust in both, statistical and economic terms to the inclusion of bank*year or loan officer*year fixed effects.

Columns (4-5) of Panel A show that loan officers smooth credit ratings independently of whether clients experience a negative or positive *Rating Shock*. Column (4) includes only observations with a *Negative Shock* (*Rating Shock* ≤ 0), while column (5) includes only observations with a *Positive Shock* (*Rating Shock* ≥ 0). The estimated coefficient of *Rating Shock* is almost identical in the two subsamples. Unreported tests confirm that there is no statistically significant difference in the magnitude of the estimated coefficient between the two subsamples. Thus, independent of whether clients' ratings are posed to increase or decrease, one out of five potential rating changes is reversed by loan officers.

Table 4-4: Smoothing of Credit Ratings

The table reports estimates of linear regressions in which *Discretion* is the dependent variable. Standard errors are clustered at the Bank*Year level and are reported in brackets. *, **, and *** indicate statistical significance of the coefficients at the 1%, 5%, and 10% level, respectively. See Table 4-1 for definitions of all variables.

Panel A: Baseline Results

Panel A, columns (1-3) present our baseline regression on the full data sample using varying sets of fixed effects for the panel regressions. Column (4) restricts the analysis to customers whose change in objective information either induces no change or a negative *Rating Shock* to the credit rating. Column (5) includes only customers whose *Rating Shock* is either zero or positive.

Dependent variable:	*Discretion*				
	(1)	(2)	(3)	(4)	(5)
Sample:	All	All	All	Negative Rating Shock	Positive Rating Shock
Rating Shock	-0.185***	-0.184***	-0.179***	-0.191***	-0.162***
	[0.0239]	*[0.0239]*	*[0.0258]*	*[0.0265]*	*[0.0268]*
Size	0.426**	0.394**	0.378**	0.447**	0.368***
	[0.167]	*[0.167]*	*[0.164]*	*[0.206]*	*[0.105]*
Calculated $Rating_{t-1}$ FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	No	No	No
Year FE	Yes	No	No	No	No
Bank * Year FE	No	Yes	No	Yes	Yes
Loan officer * Year FE	No	No	Yes	No	No
Method	OLS	OLS	OLS	OLS	OLS
R-squared	0.155	0.145	0.153	0.136	0.114
Observations	3,756	3,756	3,756	2,819	2,837

Panel B: Robustness Checks

Panel B presents robustness checks to our analysis in Panel A. In column (1), we exclude any *Rating Shocks* larger than two rating steps to see whether our restuls are mainly driven by outliers. In columns (2-3), we present our results for firms with bad proposed ratings (1-4) and good proposed ratings (5-8) in the first observation, respectively. Column (4) presents the results for observations in the years 2008 and 2009, while column (5) reports the results for observations in 2010 and 2011.

Dependent variable:	*Discretion*				
	(1)	(2)	(3)	(4)	(5)
Sample:	Excludes Shocks Larger than 2	Proposed $Rating_{t-1}$ = 1, 2, 3, 4	Proposed $Rating_{t-1}$ = 5, 6, 7, 8	2008 & 2009	2010 & 2011
Rating Shock	-0.187***	-0.188***	-0.186***	-0.182***	-0.179***
	[0.0230]	*[0.0326]*	*[0.0208]*	*[0.0362]*	*[0.0358]*
Size	0.361**	0.475*	0.361***	0.513*	0.244
	[0.163]	*[0.259]*	*[0.116]*	*[0.262]*	*[0.164]*
Calculated $Rating_{t-1}$ FE	Yes	Yes	Yes	*Yes*	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS
R-squared	0.118	0.162	0.149	0.163	0.160
Observations	3,377	1,504	2,252	2,009	1,586

Panel C: Rating Shocks Based on Small Changes to Quantitative Scores

Panel C presents estimates of the use of Discretion for different ranges of shocks to the quantitative score of a customer. Columns (1-2) present estimates for negative shocks to the quantitative score of a customer. Column (1) includes only observations with shocks to the quantitative score that range between -0.05 and -0.02. Column (2) includes all changes from -0.02 to 0. Columns (3-4) present identical sample splits for positive shocks to the quantitative score.

Dependent variable:	*Discretion*			
	(1)	(2)	(3)	(4)
	Change in Quant.	Change in Quant.	Change in Quant.	Change in Quant.
Sample:	Score € [-0.05;-0.02]	Score € [-0.02;0]	Score € [0;0.02]	Score € [0.02;0.05]
Rating Shock	-0.311***	-0.263***	-0.164**	-0.288***
	[0.0861]	*[0.0565]*	*[0.0643]*	*[0.0860]*
Size	0.0304	0.512*	0.305	0.812
	[0.260]	*[0.259]*	*[0.187]*	*[0.508]*
Calculated Rating$_{t-1}$ FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS
R-squared	0.170	0.196	0.135	0.198
Observations	468	560	628	510

4.4.3. Robustness tests

In Table 4-4, Panel B we report a range of robustness tests which confirm that our findings above are (i) not driven by outliers, (ii) are robust across rating classes, and (iii) are similar for crisis and non-crisis years. In column (1), we exclude any *Rating Shock* larger than two notches (379 observations or 10% of the sample) to rule out that our findings are driven by extreme changes in the quantitative scores. The reported coefficient for *Discretion* (-0.187***) confirms that our findings are robust in both economic and statistical terms to outliers. In columns (2-3) we divide our sample according to the initial credit rating of the borrower, i.e. *Calculated Rating*$_{t-1}$ = 1, 2, 3, 4 or *Calculated Rating*$_{t-1}$ = 5, 6, 7, 8. The point estimates for *Discretion* in these columns (-0.188***, -0.186***) suggest that our main findings are robust across risk classes of borrowers.[10]

Finally, as our sample period incorporates the recent financial crisis, we examine whether the smoothing behavior is more pronounced in the crisis years (2008-2009) as

[10] In additional unreported tests, we use *Rating Shock* interacted with a dummy on *Large Rating Shock* (1 if | *Rating Shock* | > 2; 0 otherwise), a dummy on *Bad Rating* (1 if *Calculated Rating*$_{t-1}$ = 1, 2, 3, 4; 0 otherwise), and *Crisis* (1 if year is 2008 or 2009; 0 if year is 2010 or 2011). All interaction terms prove to be statistically insignificant (*Large Rating Shock*: 0.0105 [0.0146]; *Bad Rating*: -0.00810 [0.0254]; *Crisis*: -0.00657 [0.0321]).

opposed to the post-crisis years (2010-2011). The reported coefficients for *Discretion* in columns (4-5) suggest that this is not the case.

In Table 4-4, Panel C we present further robustness tests to our baseline regression to examine whether the loan officers' behavior deliberately aims at smoothing only those shocks to firms' quantitative credit scores which have an impact on the firm's credit rating. We exploit the fact that due to the discrete nature of the rating model employed by our banks a small shock to the quantitative score of a firm may or may not induce a change in the rating class of the client, depending on whether the initial score is close to the border of two rating classes. We divide our observations into four subsamples with similar small changes in the quantitative score from the previous to the current credit assessment. More specifically, we conduct subsample analyses for observations with changes in the quantitative score that range between [+0.02; +0.05], [0; +0.02], [-0.02; 0], and [-0.02; -0.05] respectively. Keeping the change in the quantitative information in these close ranges, we are able to assess whether, for similar shocks to the quantitative information, the loan officers' smoothing is driven by those changes in quantitative scores that actually trigger a change in the rating of a customer.

The results reported in Panel C suggest that a given shock to the quantitative score of a firm is much more likely to induce the use of *Discretion* by the loan officer if it would trigger a change in the rating class of the firm. Confirming our results in Panel A and Panel B, we find a significant negative coefficient of *Rating Shock* in all six subsamples. The point estimates reported suggest that a change to the quantitative score of a client is 16% to 31% more likely to be smoothed if it induces a one-notch change in the rating class than if it has no impact on the rating class.

In Appendix 4-III we examine whether credit assessments which must be approved by a second staff member of the bank are less likely to be "smoothed" by loan officers. This robustness test is motivated by recent evidence suggesting that the hierarchical structure of a bank may affect the production and use of relation-specific information in lending (Liberti and Mian 2009, Hertzberg et al. 2010). For each credit assessment, our dataset provides information on whether the proposed rating of the loan officer was subject to approval by a colleague, i.e. a line manager or a credit officer. Three banks in our sample (Banks A, D, H) require internal approval for (almost) all credit assessments, three banks require almost no internal approvals (F, G, I), while the three remaining banks (B, C, E) have a significant share of both, approved and not approved loans. Bank internal policies referring to e.g. credit competences of loan officers, ratings, and the size of the underlying loan are the main determinants of whether an assessment is subject to approval or not. In order to avoid endogeneity issues we discard the observations from three banks (B, E, and F) in which control can be triggered by the subjective assessment of the loan officer, i.e. a rating override. We find that there is no robust relationship between internal approval and the smoothing of credit ratings. Our estimates suggest that, while control induces a more positive discretionary assessment, it has no significant impact on the loan officers' smoothing behavior.

4.5. Is the Smoothing of Credit Ratings Driven by Soft Information?

In this section we examine to what extent the smoothing of credit ratings documented in section 4.4 is driven by "soft" information available to loan officers about the creditworthiness of their clients. To this end we provide two separate analyses: First, we examine whether loan officers are more likely to smooth those *Rating Shocks* which turn out to be temporary as opposed to shocks which turn out to be more persistent. Second, we examine whether loan officers are more likely to smooth shocks which are firm-specific as opposed to shocks which affect a whole industry. If smoothing is driven by soft information about firm-specific creditworthiness we expect loan officers to be more likely to smooth temporary *Rating Shocks* and those which are firm-specific.

4.5.1. Temporary versus persistent shocks

A striking feature of the rating model applied by the banks in our sample is that there are not only many *Rating Shocks* (see Figure 4-1), but that many of these shocks are only temporary. To distinguish between temporary and more persistent shocks we exploit those observations from section 4.4.3 for which we also observe a 3rd consecutive credit assessment. We identify a *Rating Shock* as *Temporary* whenever the quantitative score between the second and the third observation partly or fully reverses the shock to the quantitative score between period t-1 and period t, i.e. *Rating Shock*$_t$. We calculate for all firms with three credit assessments the hypothetical *Calculated Rating* in period t+1, based on the quantitative score in period t+1 and the qualitative score in period t-1. We define a *Rating Shock* in period t as a *Temporary Shock* if:

$$\textit{Rating Shock}_t < \mathbf{0} \text{ and } \textit{Calculated Rating}_{t+1,\, Qual(t-1)} > \textit{Calculated Rating}_{t,\, Qual(t-1)}$$

or

$$\textit{Rating Shock}_t > \mathbf{0} \text{ and } \textit{Calculated Rating}_{t+1,\, Qual(t-1)} < \textit{Calculated Rating}_{t,\, Qual(t-1)}$$

By contrast we define a shock as *Persistent* if the shock to the quantitative score in period t is not (partly) reversed in the subsequent period t+1.[11]

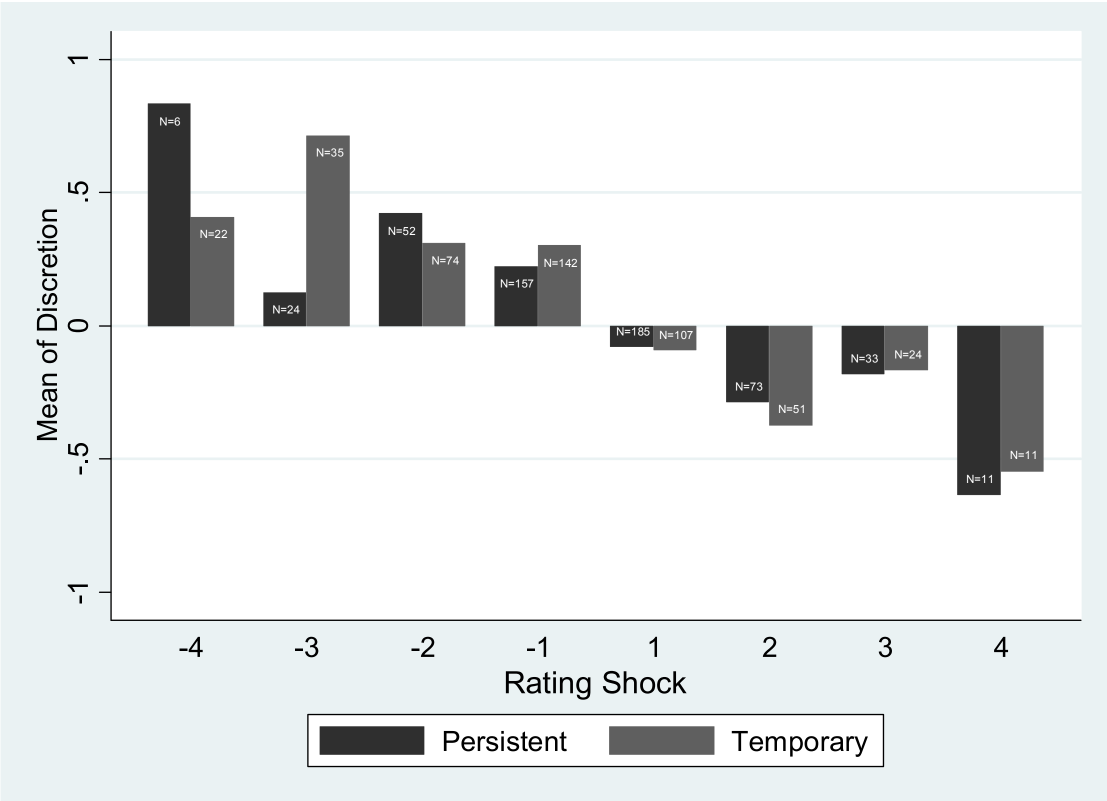
In our dataset, we have a total of 1,027 firms for which we observe three consecutive credit ratings and for which *Rating Shock*$_t \neq 0$. Our data shows that among these observations 46% of the *Rating Shocks* turn out to be *Temporary* by period t+1. The reason behind the high frequency of *Rating Shocks* and the high share of *Temporary* shocks is that the rating model employed by our banks follows a point-in-time approach to assess the creditworthiness as opposed to measuring the creditworthiness through the cycle. As a consequence the calculated rating class of a client is very sensitive to short-term changes in financial statement data.

Are loan officers able to identify temporary *Rating Shocks* and do they limit their smoothing to these cases? Figure 4-2 suggests that this is not the case. The figure displays the relation between *Rating Shock*$_t$ and *Discretion*$_t$ conditional on whether a shock turns out to be *Temporary* or *Persistent*. The figure suggests that persistent *Rating Shocks* are just as likely to be smoothed as temporary *Rating Shocks*.

[11] In unreported robustness tests we restrict *Temporary* to observations that did not (partly) reverse their *Rating Shock* in at least the following two observation. While restricting our analysis to clients with at least four consecutive observations, the tests yield similar results.

Figure 4-2: Discretion on Temporary vs. Persistent Rating Shocks

Figure 4-2 shows the mean values of *Discretion* depending on different values of *Rating Shocks*. Further, results distinguish between observations where a customer's rating will reverse its *Rating Shock* in the next period (*Temporary*) or not (*Persistent*). The analysis includes only customers with at least three observations in our initial data sample and either a positive or negative *Rating Shock* between the first and the second observation. *Rating Shocks* larger than + / - 4 are excluded from the illustration.



The multivariate analysis presented in Table 4-5 confirms that loan officers are not more likely to smooth temporary *Rating Shocks* than more persistent ones. In Panel A of the table we present estimates of our empirical model [1] separately for firms which experience temporary *Rating Shocks* (columns 1, 3, 5) and those which experience persistent *Rating Shocks* (columns 2, 4, 6). Again our main coefficient of interest is β_1 which captures the relation between *Rating Shock*$_{i,t}$ and discretionary rating changes *Discretion*$_{i,t}$. If smoothing is driven by soft-information we expect a larger (negative) estimate for β_1 in the subsample of clients with temporary shocks compared to those with persistent shocks. By contrast the estimates reported in Panel A do not yield different point estimates for β_1 when comparing firms with temporary and persistent shocks. In columns (1-2) we report estimates for firms with both positive and negative *Rating Shocks* which display almost identical coefficients for temporary (-0.197***) and persistent *Rating Shock*$_t$ (-0.218***). This result is confirmed in columns (3-4) and (5-6) for the subsample of firms with positive *Rating Shocks* and negative *Rating Shocks* respectively.[12]

Table 4-5: The Smoothing of Temporary versus Persistent Rating Shocks

The table reports estimates of linear regressions in which *Discretion* is the dependent variable. All analyses are restricted to customers with at least three observations in our initial sample and a non-zero *Rating Shock* in the second observation. Standard errors are clustered at the Bank*Year level and are reported in brackets. *, **, and *** indicate statistical significance of the coefficients at the 1%, 5%, and 10% level, respectively. See Table 4-1 for a defitinion of all variables.

Panel A: Baseline Estimates

Columns (1), (3), and (5) include all observations for which *Rating Shocks* are classified as *Temporary*. Columns (2), (4), and (6) include only observations where the *Rating Shock* is classified as *Persistent*. Columns (3-4) include only positive *Rating Shocks*, while columns (5-6) include only negative *Rating Shocks*.

Dependent variable:	*Discretion*					
	(1)	(2)	(3)	(4)	(5)	(6)
Sign of Rating shock	Positive & negative		Positive		Negative	
Type of rating shock	Temporary	Persistent	Temporary	Persistent	Temporary	Persistent
Rating Shock	-0.218***	-0.197***	-0.268**	-0.199***	-0.182**	-0.242**
	[0.0509]	*[0.0378]*	*[0.111]*	*[0.0417]*	*[0.0823]*	*[0.0934]*
Size	0.665	0.538*	-0.0925	-0.0878	1.003	1.308*
	[0.411]	*[0.314]*	*[0.244]*	*[0.354]*	*[0.585]*	*[0.632]*
Calculated Rating$_{t-1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.233	0.182	0.219	0.148	0.156	0.195
Observations	477	550	195	308	282	242

[12] In unreported additional tests, we include a term interacting *Rating Shock* with *Temporary* to test for the significance of these differences. Estimation results and standard errors confirm our interpretation of statistically insignificant differences in the full sample (-0.0301 [0.0328]), when excluding large *Rating Shocks* (-0.0134 [0.0269]), for positive initial *Rating Shocks* (-0.0805 [0.0945]), and for negative initial *Rating Shocks* (-0.0429 [0.0892]).

Panel B: Experience and the Use of Discretion

Panel B presents estimation results for different degrees of experience of either the loan officer or the bank. Odd columns further restrict the sample to observations where the initial *Rating Shock* is classified as *Termporary*. Even columns include all observation for which the *Rating Shock* is classified as *Persistent*. Columns (1-4) differentiate between two degrees of loan officers' experience. In columns (1-2) / (3-4), we include only observations of loan officers that, at the time of the rating application, filed less / more than the overall median of rating applications per loan officer. Columns (5-8) differentiate between two degrees of bank experience. Columns (5-6) include only observations of banks that use the rating tool for less than 21 months (median) at the time of the observation. Columns (7-8) include the observations where the rating model has been introduced for more than 21 months.

Dependent variable:	*Discretion*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low Experience Loan Officer		High Experience Loan Officer		Low Experience Bank		High Experience Bank	
Sample:	Temporary	Persistent	Temporary	Persistent	Temporary	Persistent	Temporary	Persistent
Rating Shock	-0.183***	-0.180***	-0.244***	-0.226***	-0.145***	-0.129***	-0.313***	-0.275***
	[0.0566]	*[0.0415]*	*[0.0616]*	*[0.0531]*	*[0.0370]*	*[0.0296]*	*[0.0547]*	*[0.0468]*
Size	0.341	0.377	1.066*	0.908	0.140	0.387*	1.153*	0.892
	[0.294]	*[0.309]*	*[0.564]*	*[0.579]*	*[0.301]*	*[0.189]*	*[0.598]*	*[0.649]*
Calculated $Rating_{t-1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.273	0.196	0.289	0.244	0.229	0.187	0.314	0.240
Observations	261	257	216	293	237	277	240	273

The apparent inability of loan officers to identify and smooth only the temporary *Rating Shocks* to their clients suggests that their use of *Discretion* is not driven by soft-information about firm-specific creditworthiness. This result may, however, be driven by the low level of experience of loan officers with this new credit rating tool. In Panel B of Table 4-5, we therefore examine whether loan officers are better at distinguishing temporary from persistent *Rating Shocks* as they become more familiar with the rating tool. Hereby, we employ both, a measure of personal experience as well as a measure of institutional experience with the rating tool. The personal experience of the loan officer is measured using the number of rating applications filed by that loan officer prior to the current application. We calculate this experience using our full dataset of 14,974 credit assessments. We classify an observation as one with *Low Experience Loan Officer* (*High Experience Loan Officer*) if the loan officer filed less than (more than) the median of applications across the total dataset at the time of the application.[13] We measure the institutional experience with the rating tool on the basis of the number of months the tool has been used in each bank prior to the current credit assessment. We divide our sample into observations with *Low Experience Bank* and *High Experience Bank* using the median experience as cut-off value.[14] Assuming that loan officers communicate their experience with the rating tool among each other, this indicator might be better able to capture common knowledge within banks about the over-sensitivity of the rating tool with regard to short-term fluctuations in quantitative scores.

The estimates presented in Panel B of Table 4-5 display two interesting findings: First, greater experience with the rating tool, especially at the institutional level seems to lead to more smoothing of *Rating Shocks*. Indeed, the estimates reported for *Rating Shock* in columns (5-8) suggest that the degree of smoothing more than doubles when a bank has been using the rating tool for more than 21 months.[15] Even though the estimated differences between the subsamples are not statistically significant, it seems

[13] The mean number of applications per loan officer is 105 with a median of 42.

[14] The mean number of number of months the tool has been used in each bank prior to the current credit assessment is 24 months. The median is 21 months. Note that, as the nine banks adopted the rating tool at different points in time, we can still include year fixed effects in both specifications to account for changes in economic conditions over time.

[15] In unreported robustness tests, we include an interaction term on *Rating Shock* * *High Experience Bank* in the regression, thus testing the differences between columns (1-2) vis-á-vis columns (3-4) and columns (5-6) vis-à-vis columns (7-8). The estimation coefficients are -0.0122 [0.0242] for the experience of the loan officer and -0.0485 [0.0424] for bank experience.

that over time the loan officers at each bank learn that the rating tool produces a significant amount of (temporary) *Rating Shock* and try to use their *Discretion* to smooth these changes. However, the Panel B results also show that neither personal nor institutional experience consistently contributes to the loan officers' ability to identify short-term fluctuations in the creditworthiness of a customer. Independent of the degree of experience of loan officers or the bank with the rating tool, we find very similar estimation results for *Rating Shock* in the subsample of temporary and persistent shocks.[16] This sheds further doubt on the hypothesis that loan officers use their discretionary power to incorporate additional information in the rating process.

We can conclude from Table 4-5 that the smoothing of credit ratings by loan officers is related to high frequency of (temporary) *Rating Shocks* inherent to the rating model. However, even loan officers do not seem to be able to single out and smooth only those *Rating Shocks* which are actually *Temporary*. This casts strong doubt on the hypothesis that loan officers use their discretionary power to incorporate additional information in the rating process.

4.5.2. Aggregate versus idiosyncratic shocks

If the smoothing of credit ratings by loan officers were driven by firm-specific information we would expect that they are more likely to smooth idiosyncratic *Rating Shocks* as compared to "macro" shocks, i.e. shocks which affect a whole industry. Previous evidence on the smoothing of credit conditions suggests that banks smooth loan rates to their clients in response to aggregate shocks to interest rates and credit risk (Berger and Udell 1992; Berlin and Mester 1998, 1999). However, there is scarce evidence on the "smoothing" of firm-specific shocks and whether banks are more likely to smooth aggregate as opposed to idiosyncratic shocks.[17] In this section we exploit differences in aggregate *Rating Shocks* across industries and years in our

[16] In unreported robustness tests, we use an interaction term on *Temporary* * *Rating Shock* to assess whether the differences between the subsamples are in fact insignificant. Supporting our interpretation, we find insignificant differences in the smoothing behavior for *Temporary* and *Persistent Rating Shocks* (Low Experience Loan Officer: -0.0385 [0.0400]; High Experience Loan Officer: -0.000580 [0.0277]; Low Experience Bank: -0.0195 [0.0357]; High Experience Bank: -0.0597 [0.0374]).

[17] Elsas and Krahnen (1998) provide some evidence that "Hausbanks" insure their clients against firm-level rating shocks, but they do not distinguish between shocks which are driven by firm-specific conditions as opposed to aggregate market conditions.

sample to examine whether the smoothing of *Rating Shocks* differs for market shocks as opposed to firm-specific shocks.

To disentangle firm-specific *Rating Shocks* from aggregate *Rating Shocks* we calculate the average share of positive and negative *Rating Shocks* for each industry in each year. We then divide our sample into two subsamples based on whether an observation is in an industry-year with a high share (top quartile) of negative *Rating Shocks* (*Bad market conditions*) or an industry-year with a high share (top quartile) of positive *Rating Shocks* (*Good market conditions*). We identify firm-specific shocks as those which are positive (negative) although the industry of the firm is experiencing bad (good) conditions.

Our empirical analysis again involves replicating our baseline model [1] for subsamples of firm-specific versus aggregate shocks. We then compare the degree of smoothing as captured by the estimated coefficient for *Rating* $Shock_t$ across subsamples. Columns (1-2) and (3-4) present estimations for the subsample observations in *Good* and *Bad market conditions* respectively. The results reported in Table 4-6 indicate that loan officers are not more likely to smooth firm-specific *Rating Shocks* than they are to smooth aggregate shocks. The point estimates reported for *Rating Shock* in columns (1-2) suggest that when market conditions are good in an industry, loan officers are more likely to smooth (idiosyncratic) negative *Rating Shocks* of a firm in that industry than they are to smooth a (aggregate) positive *Rating Shock*.

However, when market conditions are bad in an industry, loan officers are also more likely to smooth a (aggregate) negative *Rating Shock* than they are to smooth (idiosyncratic) positive *Rating Shocks*. Unreported pooled sample tests suggest that there is no significant difference in the smoothing of idiosyncratic versus aggregate *Rating Shocks* under any market conditions.[18]

[18] In unreported robustness tests, we include an interaction term on *Rating Shock* * *Negative Shock* in the analysis. The results confirm our interpretation showing differences between smoothing of idiosyncratic and aggregate rating shocks are statistically insignificant. Point estimates [and standard errors] for the interaction terms are -0.0481 [0.0463] for *Good market conditions* and 0.0564 [0.0698] for *Bad market conditions*.

Table 4-6: The Smoothing of Idiosyncratic Shocks vs. Macro Shocks

The table reports estimates of linear regressions in which *Discretion* is the dependent variable. We split our sample according to the share of positive and negative *Rating Shocks* within each industry in each year. Columns (1-2) present the results for observations with above-average market conditions, i.e. those industry-years with the highest quartile of positive *Rating Shocks*. Columns (3-4) include only observations with below-average market conditions, i.e. those industry-years with the highest quartile of negative *Rating Shocks*. Columns (1) and (3) present the results for firms with a positive *Rating Shock*, columns (2) and (4) present the results for firms with a negative *Rating Shock*. Standard errors are clustered at the Bank*Year level and are reported in brackets. *, **, and *** indicate statistical significance of the coefficients at the 1%, 5%, and 10% level, respectively. See Table 4-1 for a defitinion of all variables

Dependent variable:	*Discretion*			
	(1)	(2)	(3)	(4)
	Good Market Conditions		Bad Market Conditions	
Sample:	Positive Rating Shock	Negative Rating Shock	Positive Rating Shock	Negative Rating Shock
Rating Shock	-0.147***	-0.214***	-0.193***	-0.233***
	[0.0391]	*[0.0587]*	*[0.0408]*	*[0.0392]*
Size	0.481**	0.422***	0.443*	0.316
	[0.204]	*[0.153]*	*[0.231]*	*[0.287]*
Calculated Rating$_{t-1}$ FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS
R-squared	0.112	0.221	0.171	0.230
Observations	751	626	626	728

4.6. Is Smoothing Driven by Insurance Considerations?

The theory of implicit contracts suggests that loan officers may smooth the credit ratings of their clients in order to insure these clients against changes in lending terms. This theory would predict that the smoothing of clients' ratings is more likely to occur when lending terms, i.e. interest rates and credit limits, are sensitive to changes in rating classes. In this section we first exploit differences in loan pricing regimes across banks to examine whether smoothing of ratings is more common at banks where interest rates are more sensitive to rating changes. We then exploit non-linearities in loan pricing within pricing regimes to examine whether *Rating Shocks* which have a stronger impact on interest rates are more likely to be smoothed. In line with the theory on implicit contracts, we find strong evidence for insurance across banks and across pricing-regimes. Our analysis within banks suggests that this insurance favors the bad customer segment at the expense of the initially good clients.

4.6.1. Smoothing across pricing regimes

While all nine banks in our sample employ the same rating tool for small business clients, they differ substantially with respect to how rating classes impact loan terms. In particular, interest rates on loans are explicitly tied to rating classes at some banks, while they are unrelated to rating classes at other banks. Based on a questionnaire sent to all banks, as well as on expert interviews with the provider of the rating tool we classify each bank according to how sensitive their interest rates are to credit ratings. The provider of the rating tool also offers a pricing tool to all banks which calculates risk-adjusted interest rates accounting for expected credit loss and capital costs. The dummy variable *Pricing Tool* indicates that a bank makes use of the pricing tool for all rating applications. In our sample, this is the case for Bank C, E, and G, (see Table 4-3) at which the pricing tool is used to calculate base rates for the negotiation of loan terms with the client. *Risk-adjusted Pricing* is a dummy variable indicating that a bank uses the calculated rating class for the risk adjustment of interest rates, but that this adjustment is not based on the pricing tool offered by the provider of the rating tool. This is the case for the banks A, B, F, H and I. Finally as the benchmark case, one bank in our sample (Bank D) reports that credit ratings have *No Influence* on interest rates.

Figure 4-3 suggests that banks at which interest rates are more sensitive to rating classes are characterized by more "smoothing" of ratings. The figure plots the mean value of *Discretion* against *Rating Shock* for the three pricing regimes represented in our sample: *Pricing Tool, Risk-adjusted Pricing,* and *No Influence*. If loan officers are more inclined to smooth credit ratings of customers when the pricing of loans is more sensitive to *Rating Shocks*, we should observe the strongest (negative) correlation between *Discretion* and *Rating Shock* for the banks with *Pricing Tool* and the weakest correlation for the bank with *No Influence.* This is exactly what we find: Loan officers appear to engage in distinctively more smoothing when *Rating Shocks* would have a stronger impact on interest rates.

Figure 4-3: Pricing Regime and Discretionary Rating Changes

This figure presents the mean values of *Discretion* across different *Rating Shocks* for different levels of pricing implication (*No Influence*, *Risk-Adjusted Pricing*, *Pricing Tool*). *Rating Shocks* larger than +/- 4 are excluded from the illustration. For definitions of all variables, see Table 4-1.

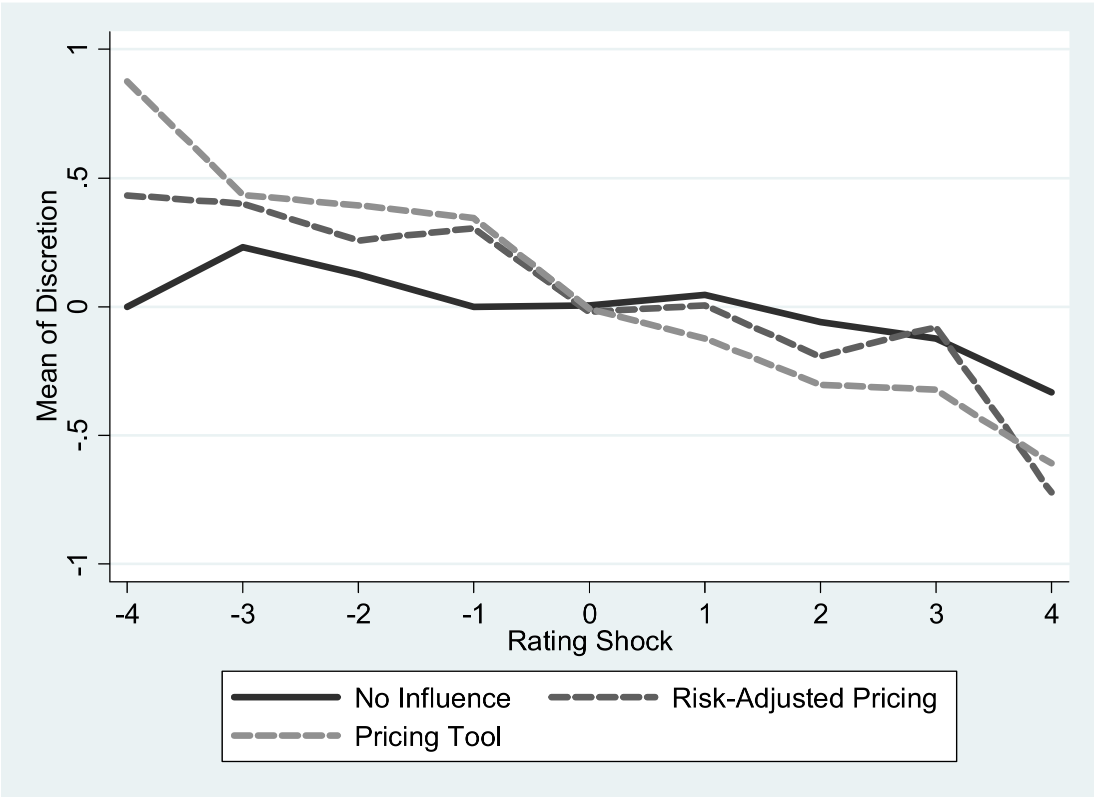


Table 4-7, Panel A presents our multivariate analysis relating the impact of pricing regimes on the smoothing of credit ratings in our empirical model [1]. We present individual estimation results for the subsamples *Pricing Tool* (columns 1, 4, and 7)*, Risk-adjusted Pricing* (columns 2, 5, and 8)*, and No Influence* (columns 3, 6, and 9). Columns (1-3) present the results for our total sample, columns (4-6) and columns (7-9) restrict the analyses to positive *Rating Shocks* and negative *Rating Shocks* respectively. Columns (1-3) show that, considering all observations, the smoothing of credit ratings is most pronounced at the banks with the *Pricing Tool* followed by the banks with *Risk-adjusted Pricing.* The bank with *No Influence* of rating results on lending terms shows the lowest degree of smoothing. The point estimates suggest substantial differences in the magnitude of smoothing across pricing regimes. A one notch *Rating Shock* to a client has a 23% probability of being reversed by the loan officer at the three banks which employ the *Pricing Tool* of the rating provider. By contrast this probability is only 16% at the five banks which use other *Risk-adjusted Pricing* models and a mere 7% at Bank D which does not practice risk-adjusted pricing. Thus going from a pricing regime at which rating changes have no influence on interest rates to a regime where they automatically induce interest rate changes roughly triples the smoothing of ratings, irrespective of the initial credit rating of the firm or the direction of the *Rating Shock* experienced by the firm.[19] Columns (4-9) consider the smoothing of positive and negative *Rating Shocks* separately and we find similar patterns: the magnitude of smoothing is consistently the highest at the banks with *Pricing Tool,* the bank with *No Influence* shows the lowest coefficient.

4.6.2. Do loan officers really care about their clients' funding costs?

The results of Table 4-7, Panel A provide support for the existence of implicit contracts whereby loan officers use their Discretion to smooth interest rates for their clients. However, the stronger smoothing of *Rating Shocks* at banks which have more risk-sensitive pricing regimes can also be rationalized by other mechanisms.

First, loan officers may simply be reluctant to convey bad news, i.e. interest rate hikes to their clients.[20] However, our evidence shows that loan officers are equally likely to smooth positive and negative Rating Shocks. The smoothing of positive *Rating Shocks* is incompatible with a reluctance to convey bad news. Second, loan officers may fear that changes in interest rates may lead borrowers to change to a competitor bank. Again though, the fact that positive and *Rating Shocks* are equally likely to be smoothed seems incompatible with a fear of competition. Borrowers are arguable more likely to switch banks in case of an interest rate hike than an interest rate decrease. Third, loan officers may be reluctant to communicate price changes in both directions because they cannot justify these changes in front of the borrower.

[19] In unreported additional analyses, we include an interaction term on *Rating Shock* and *Pricing tool*, as well as an interaction term on *Rating Shock* and *Risk-adjusted Pricing* in our baseline regression. The results suggest that the differences in the estimation coefficients are statistically significant across different subsamples with the baseline effect of *Rating Shock* equaling -0.105***. At the banks with *Risk-adjusted Pricing*, this coefficient is increased by -0.0580*. At the banks with the *Pricing Tool*, the increase amounts to -0.112***. Similar values result from the analyses for positive and negative *Rating Shocks*.

[20] Rosen and Tesser (1970) provide first empirical evidence for this MUM effect "that the reluctance to transmit information is directly dependent on the inferred desirability of the message for the potential recipient."

Loan officers may smooth *Rating Shocks* not because of the actual price implications for their clients, but because they lack convincing arguments to support the proposed interest rate changes. Such behavior seems very plausible for our sample of banks, given that loan officers appear to know that the rating model leads to a high frequency of (often temporary) *Rating Shocks*.

As a final exercise in our analysis we try to disentangle whether the observed smoothing of credit ratings is driven by pure insurance considerations, i.e. the concern about the volatility of lending terms for borrowers, or rather by a reluctance to communicate frequent and, from the viewpoint of the loan officer, hard-to-justify price changes. In order to do so we exploit the fact that probabilities of default and thus risk-adjusted credit spreads are linked to rating classes in a non-linear manner. This implies that a given *Rating Shocks* will lead to a stronger price change if the initial rating of the borrower is lower. Accordingly, if smoothing is triggered by pure insurance considerations, we should find that a given *Rating Shock* is more likely to be smoothed if the borrower has a low rating.

To test this hypothesis, we replicate our initial regressions of Panel A, adding an interaction term of *Rating Shock* with *Calculated* $Rating_{t-1}$ = 1, 2, 3, or 4 to all specifications. If the smoothing behavior by loan officers is driven predominantly by pure insurance considerations we expect a significant negative coefficient for this interaction term, in particular for those banks with a close tie between rating result and loan rates.

Table 4-7: Pricing Impact and the Smoothing of Credit Ratings

This table reports estimates of linear regressions with *Discretion* as dependent variable. Standard errors are clustered at the Bank*Year level and are reported in brackets. *, **, and *** indicate statistical significance of the coefficients at the 1%, 5%, and 10% level, respectively. See Table 4-1 for definition of all variables.

Panel A: Difference in Pricing Regimes across Banks

Panel A, columns (1), (4), and (7) include observations from banks with the strongest tie between rating result and interest rates, i.e. the *Pricing Tool*. Columns (2), (5), and (8) include all banks that use *Risk-Adjusted Pricing*, columns (3), (6), and (9) include the banks with *No Influence* of the rating result on interest rates. Additionally, columns (4-6) include only positive *Rating Shocks*, while columns (7-9) include only negative *Rating Shocks*.

Dependent variable:	*Discretion*								
	All			Positive Rating Shock			Negative Rating Shock		
Sample:	Pricing Tool (Bank C, E, G)	Risk-adjusted Pricing (Bank A,B, F, H, I)	No Influence (Bank D)	Pricing Tool (Bank C, E, G)	Risk-adjusted Pricing (Bank A,B, F, H, I)	No Influence (Bank D)	Pricing Tool (Bank C, E, G)	Risk-adjusted Pricing (Bank A,B, F, H, I)	No Influence (Bank D)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rating Shock	-0.229***	-0.161***	-0.0685**	-0.214***	-0.113**	-0.0679**	-0.229***	-0.176***	-0.0870
	[0.0400]	*[0.0363]*	*[0.0170]*	*[0.0398]*	*[0.0437]*	*[0.0172]*	*[0.0441]*	*[0.0416]*	*[0.0535]*
Size	0.762**	-0.0134	-0.0461	0.573***	0.173	0.175*	0.832**	-0.0203	-0.0978
	[0.272]	*[0.112]*	*[0.175]*	*[0.186]*	*[0.123]*	*[0.0636]*	*[0.317]*	*[0.0993]*	*[0.163]*
Calculated Rating$_{t-1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.192	0.153	0.128	0.166	0.115	0.205	0.174	0.155	0.129
Observations	2,003	1,384	369	1,532	1,025	280	1,506	1,042	271

Panel B: Difference in Pricing Regimes within Banks

Panel B reports estimates of linear regressions with Discretion as dependent variable. The panel present the same analyses as Panel A, adding an interaction term on Rating Shock * Proposed Rating t-1 = 1, 2, 3, 4 to all regressions.

Dependent variable:	*Discretion*								
	All			Positive Rating Shock			Negative Rating Shock		
Sample:	Pricing tool (Bank C, E, G)	Risk-adjusted pricing (Bank A,B, F, H, I)	No influence (Bank D)	Pricing tool (Banks C, E, G)	Risk-adjusted pricing (Bank A,B, F, H, I)	No influence (Bank D)	Pricing tool (Bank C, E, G)	Risk-adjusted pricing (Bank A,B, F, H, I)	No influence (Bank D)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rating Shock	-0.234***	-0.146***	-0.0806	-0.433***	-0.188***	-0.0236	-0.205***	-0.146***	-0.0984
	[0.0270]	*[0.0308]*	*[0.0501]*	*[0.0558]*	*[0.0495]*	*[0.0478]*	*[0.0328]*	*[0.0368]*	*[0.0568]*
Rating Shock * ProposedRating$_{t-1}$ = 1, 2, 3, 4	*0.0110*	*-0.0324*	*0.0209*	*0.258****	*0.0846*	*-0.0476*	*-0.185*	*-0.335***	*0.0698*
	[0.0352]	*[0.0280]*	*[0.0646]*	*[0.0407]*	*[0.0683]*	*[0.0520]*	*[0.122]*	*[0.120]*	*[0.133]*
Size	0.765**	-0.0176	-0.0456	0.615***	0.176	0.174**	0.835**	0.00234	-0.115
	[0.269]	*[0.111]*	*[0.170]*	*[0.188]*	*[0.122]*	*[0.0590]*	*[0.314]*	*[0.0954]*	*[0.173]*
Calculated Rating$_{t-1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.192	0.154	0.129	0.179	0.117	0.205	0.180	0.177	0.132
Observations	2,003	1,384	369	1,532	1,025	280	1,506	1,042	271

The results reported in Table 4-7, Panel B cast doubt on the hypothesis that the smoothing of credit ratings is driven by pure insurance considerations. We do not find robust evidence that *Rating Shocks* to clients with low initial ratings are more likely to be smoothed. Moreover, we do not find evidence that the differential smoothing behavior for clients with low initial ratings is strongest among those banks with the most risk-sensitive pricing. Estimation results in columns (1-3) show virtually no correlation between *Discretion* and our interaction term on *Rating Shock* and *Calculated* $Rating_{t-1}$ *= 1, 2, 3, or 4*. There are also no relevant differences between the estimation results across different pricing regimes. In columns (4-6) and (7-9) we report separate results for clients with positive *Rating Shocks* and negative *Rating Shocks* respectively. The columns (4-6) suggest that positive shocks to low rated clients are not more likely to be smoothed than positive shocks to high rated clients. The column (7-9) results suggest that at banks with risk-sensitive interest rates, loan officers are more likely to smooth negative shocks (i.e. potential interest rate increases) for low-rated clients. However, counter to our expectations the coefficient of the interaction term *Rating Shock* * $ProposedRating_{t-1}$ *= 1, 2, 3, or 4* is smaller for the banks which use the *Pricing Tool* than for those which have other *Risk-adjusted Pricing* mechanisms. Moreover, the interaction term is only statistically significant for the latter banks.

Overall, the results in Table 4-7 suggest that the smoothing of credit ratings by loan officers insures borrowers against interest rate changes. The Panel A estimates provide strong evidence that smoothing is more common when interest rates are more risk-sensitive. However, the Panel B results suggest that it would be false to conclude that the sole motivation behind the smoothing of credit ratings is an implicit contract according to which loan officers purposely insure their clients against volatility in interest rates. It seems equally likely that loan officers are reluctant to communicate interest rate changes based on the frequent rating changes inherent to this point-in-time credit rating model. Loan officers thus seem to be insuring their borrowers against the volatility of the rating model rather than volatility of interest rates.

4.7. Conclusions

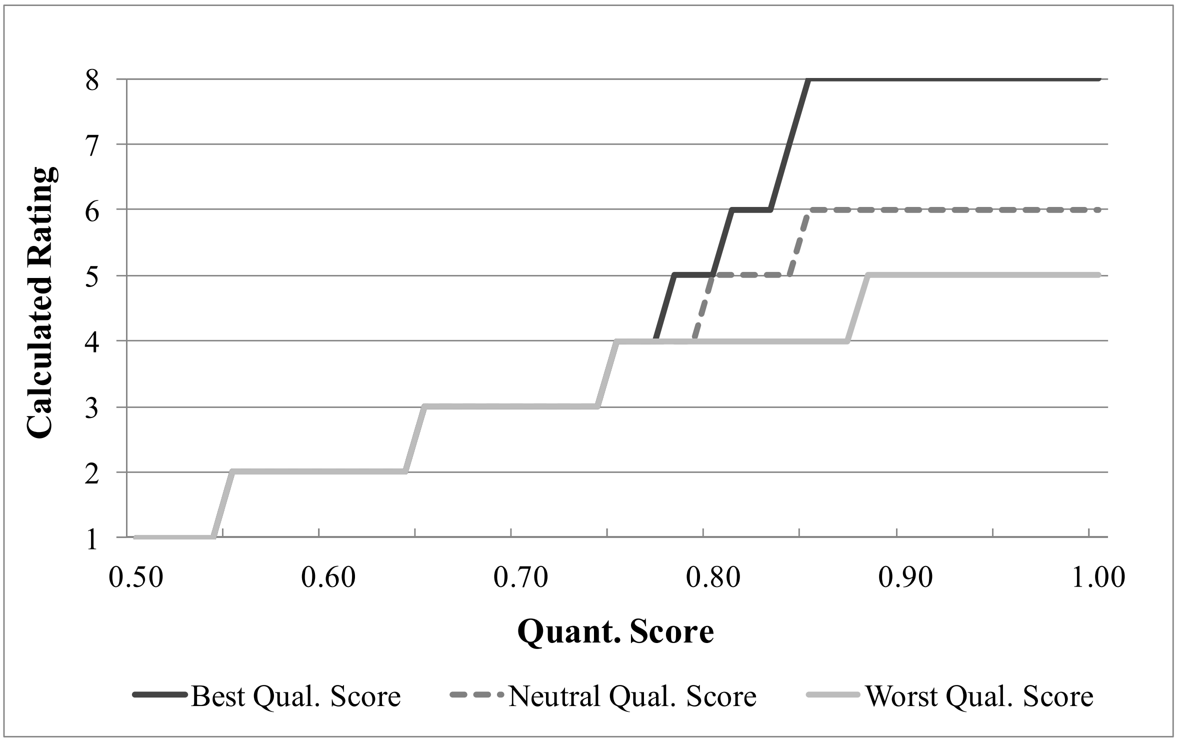
In this paper we examine to what extent loan officers use their *Discretion* to smooth shocks to the credit ratings of their clients. We find that 18% of all rating changes induced by changes in the quantitative scores of clients are reversed by loan officers - independent of whether a client experiences a positive or negative shock.

We find that the smoothing of credit ratings is not compatible with the view that loan officers are adding valuable firm-specific soft information to the credit assessment process: Loan officers are equally likely to smooth temporary and persistent *Rating Shocks* as well as firm-specific and macro *Rating Shocks*. Our results are compatible with an insurance view of credit relationships: Loan offers are more likely to smooth *Rating Shocks* when these have stronger price implications for the borrower. However, the smoothing of price-relevant *Rating Shocks* does not seem to be driven by implicit contracts between loan officers and their clients. Instead, our results suggest that what looks like an implicit insurance contract is most likely the result of loan officers' reluctance to communicate interest rate changes based on a credit model which produces frequent and often temporary rating changes.

Our results have important practical implications for banks and regulators: Our results raise doubt about the effectiveness of credit assessment models in which credit ratings react strongly to contemporary changes in financial ratios. It seems that loan officers use their discretion to convert such "point-in-time" models to a "through-the-cycle" model, however without improving upon the informational efficiency of the credit assessment process. This should also make regulators wary of internal credit rating models. The use of internal credit rating processes under Basel II (and Basel III) relies on the assumption that these processes make efficient use of the available information on clients' creditworthiness. If loan officers use their discretionary power in the credit assessment process to reduce the volatility of the rating model rather than to improve its predictive power, the efficiency of rating models which provide strong discretion to loan officers may be questioned.

Appendix 4-I: Calculated Rating as a Function of Quantitative Score and Qualitative Score

Appendix 4-I presents the conversion mechanics from the quantitative scores to the calculated rating. The different lines represent the rating results for a hypothetical rating with a best, worst and neutral qualitative assessment. Quantitative scores below 0.5 result in a calculated rating of one, irrespective of the qualitative score. For a detailed definition of the variables, see Table 4-1.



Appendix 4-II: Exemplary Rating Application Form

Appendix 4-II presents a stylized design for the graphical user interface of the rating tool for SMEs used at the banks in our data sample. The first section includes basic information on the customer and the date of the application. This section also reports the calculated rating score and the resulting calculated rating. The second section requires the loan officer to input the relevant quantitative information on the customer. For each of the seven different ratios, the quantile the current customer is in, is displayed. Besides the ratios, the rating model also includes additional quantitative information on two items that need to be answered categorically. The following section processes the qualitative information on the customer. Each question is designed to choose between three to four categorical assessments. In the final section, the loan officer may calculate the rating and potentially redo his / her assessment before proceeding and saving the results.

Credit Rating Application for SMEs

Customer:	XXX
Date of Financial Statement:	MM/DD/YYYY
Date of Rating:	MM/DD/YYYY
Calculated Rating	
Calculated Score	

Input for Quant. Score

		Quantile 1	2	3	4	5
Ratio 1	x%					
Ratio 2	x%					
Ratio 3	x%					
Ratio 4	x%					
Ratio 5	x%					
Ratio 6	x%					
Ratio 7	x%					

Additional Information 1	category 1 / category 2 / category 3
Additional Information 2	category 1 / category 2 / category 3

Input for Qual. Score

Qual. Score 1	good / average / weak
Qual. Score 2	good / above average / average / below average / weak
Qual. Score 3	very good / good / average / weak
Qual. Score 4	good / average / weak
Qual. Score 5	good / average / weak
Qual. Score 6	good / average / below average / weak / very weak
Qual. Score 7	very good / good / average / weak

Calculate Rating

Save & Proceed

Appendix 4-III: Impact of Control on Discretionary Rating Changes

This table reports the estimates of linear regressions with *Discretion* as dependent variable. Standard errors are clustered at the Bank*Year level and are reported in brackets. *, **, and *** indicate statistical significance of the coefficients at the 1%, 5%, and 10% level, respectively. *Control* is a dummy variable taking the value one if a second person is responsible for reviewing and approving the rating proposed by the loan offier and zero otherwise. Regressions only include observations of banks that do not assign *Control* based on a potential override. Column (1) reports the results for the complete sample. Column (2) uses only observations that experienced a negative *Rating Shock* to the objective credit information. Column (3) uses only observations with a positive *Rating Shock*. See Table 4-1 for a defition of all variables.

Dependent variable:		*Discretion*	
Firms:	All	Negative Rating Shock	Positive Rating Shock
	(1)	(2)	(3)
Rating Shock	-0.213***	-0.166*	-0.263**
	[0.0707]	*[0.0801]*	*[0.100]*
Control	0.156***	0.112	0.127**
	[0.0446]	*[0.0693]*	*[0.0532]*
Rating Shock * Control	-0.00275	-0.0627	0.0796
	[0.0655]	*[0.0768]*	*[0.0869]*
Size	0.0847	0.106	0.240**
	[0.0933]	*[0.0984]*	*[0.113]*
Calculated $Rating_{t-1}$ FE	Yes	Yes	Yes
Bank * Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Method	OLS	OLS	OLS
R-squared	0.202	0.209	0.165
Observations	1,938	1,437	1,437

References

Agarwal, S. & R. Hauswald (2010a): "Distance and Private Information in Lending", *Review of Financial Studies* 23, 2757-2788.

Agarwal, S. & R. Hauswald (2010b): "Authority and Information", Working Paper.

Azariadis C. (1975): "Implicit Contracts and Underemployment Equilibria", *Journal of Political Economy* 83, 1183–1202.

Bailey, M. N. (1974): "Wages and Employment under Uncertain Demand", *Review of Economic Studies* 41, 37–50.

Berg, T., Puri, M. & Rocholl, J. (2012): "Loan Officer Incentives and the Limits of Hard Information", Working Paper.

Berger, A.N. & G.F. Udell (1992): "Some evidence on the empirical significance of credit rationing", *Journal of Political Economy* 100, 1047-1077.

Berger, A.N. & G.F. Udell (1995): "Relationship lending and lines of credit in small firm finance", *Journal of Business* 68, 351–381.

Berger, A., N. H. Miller, M. A. Petersen, R. Rajan & J.C. Stein (2005). "Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks", *Journal of Financial Economics* 76, 237-269.

Berlin, M. & L. Mester (1998): "On the Profitability and Cost of Relationship Lending", *Journal of Banking & Finance* 22, 873-897.

Berlin, M. & L. Mester (1999): "Deposits and relationship lending", *Review of Financial Studies* 12, 579–607.

Cerquiero, G., H. Degryse & S. Ongena (2011): "Rules versus discretion in loan rate setting", *Journal of Financial Intermediation* 20, 503-529.

Cole, R.A. (1998): "The importance of relationships to the availability of credit", *Journal of Banking & Finance* 22, 959–977.

Degryse, H. & P. Van Cayseele (2000): "Relationship lending within a bank-based system: Evidence from European small business data", *Journal of Financial Intermediation* 9, 90-109.

Degryse H., J. Liberti, T. Mosk & S. Ongena (2011): "The added value of soft information", Working Paper.

Elsas, R. & J. P. Krahnen (1998): "Is relationship lending special? Evidence from credit-file data in Germany", *Journal of Banking & Finance* 22, 1283-1316.

Fried, J. & P. Howitt (1980): "Credit rationing and implicit contract theory", *Journal of Money, Credit, and Banking* 12, 471-487.

Grunert, J., L. Norden, L. & M. Weber (2005): "The Role of Non-Financial Factors in Internal Credit Ratings", *Journal of Banking and Finance* 29, 509-531.

Harhoff, D. & T. Körting (1998): "Lending relationships in Germany: Empirical results from survey data", *Journal of Banking and Finance* 22, 1317–54.

Hertzberg, A., J.M. Liberti & D. Paravasini (2010) : “Information and Incentives Inside the Firm: Evidence from Loan Officer Rotation”, *Journal of Finance* 65, 795-828.

Ioannidou, V. & S. Ongena (2010): “Time for a Change: Loan Conditions and Bank Behavior when Firms Switch Banks”, *Journal of Finance* 65, 1847-1877.

Liberti, J. M. & A. R. Mian (2009): “Estimating the Effect of Hierarchies on Information Use”, *Review of Financial Studies* 22, 4057–4090.

Petersen, M. A & R.G. Rajan (1994): “The Benefits of Lending Relationships: Evidence from Small Business Data”, *Journal of Finance* 49, 3-37.

Petersen, M.A. & R.G. Rajan (1995): “The effect of credit market competition on lending relationships”, *Quarterly Journal of Economics* 110, 407-443.

Rosen, S. & Tesser, A. (1970): “On Reluctance to Communicate Undesirable Information: The MUM Effect”, *Sociometry* 33 (3), 253 – 263.

Qian, J., P. E. Strahan, P. E. & Z. Yang, Z. (2010): “The Impact of Organizational and Incentive Structures on Soft Information: Evidence from Bank Lending”, Working Paper.

Scott, J.A. (2006): “Loan officer turnover and credit availability for small firms”, *Journal of Small Business Management*, 544–562.

Sharpe, S. A. (1990): “Asymmetric Information, Bank Lending, and Implicit Contracts: A Stylized Model of Customer Relationships”, *Journal of Finance* 45, 1069-87.

Stein, J. C. (2002): “Information Production and Capital Allocation: Decentralized vs. Hierarchical Firms”, *Journal of Finance* 57, 1891-1921.

Stiglitz, J. E. & A. Weiss (1983): “Incentive effects of terminations: Applications to the credit and labor markets”, *American Economic Review* 73, 912–927.

Uchida, H., G. Udell & N. Yamori (2012): “Loan Officers and Relationship Lending to SMEs”, *Journal of Financial Intermediation* 21, 97-122.

Von Thadden, E. (2004): “Asymmetric information, bank lending, and implicit contracts: The winner’s curse”, *Finance Research Letters* 1, 11-23.

5. Good Cop or Bad Cop - Does Control in Small Business Lending Lead to More Efficient Credit Assessments or Crowd-Out Loan Officer Motivation?

Matthias Schaller*

This Draft: November 2012

Abstract

Using proprietary data on 3,360 credit assessments for small business clients at six different Swiss banks, we analyze how the use of control affects bank-internal credit rating processes. In line with the theory on hidden costs of control (Falk and Kosfeld 2006) and in contrast to findings on the positive impact of control for rating assessments (Hertzberg et al. 2010), we find that loan officers rate clients more positively when they are controlled by a second person. Our results further indicate that this bias is rooted in the loan officers' anticipation of potential corrections under control: More experienced loan officers not only show a stronger bias to improve a client's rating, they also use less observable means for manipulating the rating outcome. In addition, loan officers learn from their experience under control and assign more positive ratings when they were frequently corrected in the past. When measured from a cost perspective, we find that the efficiency of the rating process decreases under control: While the resulting ratings under control are hardly distinguishable from uncontrolled ratings, they consume significantly more of the bank employees' resources.

Keywords: Control, Organizational Design, Motivation, Financial Institutions

JEL classification numbers: G21, L14, D82.

---

* University of St. Gallen, Switzerland (e-mail: matthias.schaller@unisg.ch).

Acknowledgements: I thank Martin Brown, Christian Schmid, Markus Heusler, Matthias Hoffmann, Simone Westerfeld, participants at the International Doctoral Seminar for Banking and Finance in Liechtenstein, as well as seminar participants at the University of St. Gallen for their valuable input and feedback. I thank Jochen Maurer and Marcus Kahler for their assistance in preparing the data.

5.1.Introduction

Accounting literature distinguishes between two different internal control measures in hierarchical organizations: Detective and preventive control (Romney and Steinbart, 2009; Christ et al. 2008; 2012). Detective control is designed to "discover problems after they occur", preventive control measures "deter problems before they arise" (Romney and Steinbart 2009, p. 200). While preventive control restricts the employees' autonomy in an assigned task (Christ et al. 2012), detective control is typically only able to provide delayed feedback (Christ et al. 2008). Even though banks are arguably among the most regulated industries, with measures on internal control taking up a significant share of regulatory frameworks (see, for example, Banking Committee on Banking Supervision 1998), it is interesting to note that this differentiation on the concept of control did not make its transition into banking or economic literature as well as into the formalizations of regulatory frameworks.

In a recent study, Hertzberg et al. (2010), for instance, find that control induces more efficient credit ratings in small business lending. In their setting, control over a loan officer's assessment is dependent on the random assignment of job rotation among loan officers. In anticipation of their assessment being controlled by the newly assigned loan officer, current loan officers iteratively incorporate negative information in the credit rating that they would withhold without control. In contrast to these findings, Kosfeld and Falk (2006) find in an experimental setting that control tends to entail hidden cost. Their experiment allows the principal to control the agents by ruling out their most opportunistic behavior. Their results show that agents who are controlled by the principal perform significantly worse in an assigned task. This effect, however, only materializes if the principal willingly decides to control the agent. Thus, control as a sign of mistrust apparently crowds-out the intrinsic motivation of the agent.

While these results might seem contradictory at first, they are less puzzling with the two different concepts of control in mind: In Kosfeld and Falk (2006), control is designed preventive with the possibility to actively influence the agents' behavior. In Hertzberg et al. (2010), control is designed detective with the loan officer being autonomous in its initial decision and the initial rating assigned to a client. In the consequence, the different settings in both studies also provide different incentives to the agents, apparently either resulting in a positive or a negative assessment of control. At this point, banking literature does not explicitly make this distinction and hence does not provide any empirical evidence, if the opposing results of both studies are solely driven by the different concepts of control or if they can be attributed to the peculiarities of the banking industry.

Even though banking literature does not explicitly distinguish between preventive and detective control mechanisms, both measures are typically in place in banking institutions at the same time. Most internal control mechanisms in the area of a bank's risk management typically use preventive control. Risk management with the proclaimed goal to "be proactive and anticipate risks before they are experienced" (Ledgerwood and White 2006, p. 375) requires the controlling instance to be able to take active influence in a process. In contrast, auditing activities as well as employee evaluations mostly rely on detective control measures. Our study closes the gap of current research, extending the empirical implications of control in the banking environment to a preventive concept of control.

In addition to the studies by Hertzberg et al. (2010) and Falk and Kosfeld (2006), our paper is related to two other strands of literature: First, we contribute to the literature on the effect of bank organization with regard to the use of information. Stein (2002) models information use within organizations with different hierarchical structures. The model shows that decentralized firms should be better able to process soft information, whereas firms with large hierarchies perform better when information is easily quantifiable and transmittable. These predictions are supported by empirical evidence in Berger et al. (2005) and Uchida et al. (2011). A related stream of literature extends the link between information use and organizational hierarchies to geographical distance. Liberti and Mian (2009) provide evidence that the use of soft information in credit assessments depends on the geographical distance between the data collecting agent and the loan officer, with more separated institutions relying on easily verifiable information. Agarwal and Hauswald (2010) show that the geographical distance between a client and a bank has a significant impact on the creation of relationship-specific information. Our findings complement this literature by showing that a more hierarchical attribution of competencies in rating processes may have distorting effects on the loan officers' behavior leading to an overall inferior efficiency in the organizational process.

Second, we contribute to literature on the use of soft versus hard information in bank lending and credit ratings. Grunert et al. (2005) find that the combined use of financial and non-financial data results in more accurate predictions of future default. Scott (2006) provides evidence that soft information facilitates the availability of loans to small firms. In particular, the study shows that loan officers are more likely to grant loans to small firms when they gather more soft information about the firm. Degryse et al. (2012) show that the credit limits loan officers extend to their clients are highly sensitive to the qualitative assessments. Studies by Cerquiero et al. (2011) and Qian et al. (2010) show that soft information has an important impact on the lending terms. This is especially true for small, opaque, and young firms. Our findings complement this literature by showing that the use of soft information may not always contribute to more efficient credit ratings. In contrast, we find that the lack of verifiability in soft information allows loan officers to strategically bias their assessments for opportunistic purposes.

Finally, in a very recent study, Berg et al. (2012) find strong evidence for manipulating behavior of loan officers during the credit rating process. They show that loan officers iteratively alter input parameters in a rating model that solely depends on quantitative information in order to end up with, from the client's perspective, more favorable rating results. Even though our setting does not assume that the manipulation of quantitative information is a viable strategy for loan officers - as our setting allows distinctively less obvious manipulations - their results indicate that our findings might in fact be a conservative approximation of the true bias in the loan officers' behavior.

The remainder of this article proceeds as follows: The next section presents the data used in our empirical analysis. Section 3 gives a brief introduction to the credit rating process that is used in our empirical setting. Section 4 presents our results on the impact of control on the credit assessments by loan officers. Section 5 shows how approvers react to the loan officers' use of discretion. Section 6 shows how the loan officers' behavior changes over time and with increasing experience. Section 7 presents evidence how controlling credit rating applications affects the efficiency of rating processes. Section 8 concludes.

5.2. Data

Our study uses proprietary information on credit applications from 3’360 small- and medium-sized enterprises (SMEs) in Switzerland. All banks use an identical credit rating model that was created and is serviced by an external provider. We define SMEs as all corporate clients with an annual turnover of up to ten million Swiss Francs.[21] The data covers all relevant information on client-related input parameters of the rating process as well as detailed information on the results of each step in the rating process. Table 5-1 presents details and definitions on all variables used in our empirical analyses. Table 5-2 provides corresponding summary statistics. The data includes all rating applications of SMEs at six Swiss, regionally focused commercial banks covering the period since adoption of the new credit rating model to 2011. The banks in the sample introduced the credit rating model at different points in time with the first bank starting in 2006; two banks starting in 2007, two banks starting in 2008, and one bank starting in 2009. Additionally, all banks differ in size with balance sheet totals ranging from 3 to 39 billion Swiss Francs, resulting in a heterogeneous distribution of observations across banks (see Table 5-3).

Table 5-3 also indicates the use of control within the banks in our sample. Overall 73% of all rating applications are controlled by a second person. These values vary substantially between banks. Banks A, C, and E almost exclusively control their rating applications, while Banks D and F usually refrain from controlling loan officers during the application process. Bank B uses control and no-control almost evenly. Abstracting from the apparent differences in bank policies regarding the general use of control, other rules for assigning control typically use the experience of loan officers, their qualifications, the loan size a client applies for, or also the customers’ industry. It is important to note, however, that loan officers know at the beginning of a rating application whether the rating will be reviewed by a second person.

[21] For the period 2006 to 2011, 1CHF ranged between 0.75 USD and 1.30 USD.

Table 5-1: Definition of Variables

This table presents definitions for all variables used throughout our empirical analyses.

Category	Variable	Definition
Rating Process	Control	Dummy variable (0; 1), indicating if the rating results needs to be finally approved by a person other than the loan officer
	Loan Officer	Person responsble for the loan process with a particular client. Each loan officer is identified using a unique dummy variable.
	Approver	Person responsible for the ultimate approval of the rating result for a particular client. Each approver is identified using a unique dummy variable. Not defined for rating application under no-control.
Rating Scores	Quantitative Score	Rating score [0; 1] resulting from the balance sheet and income statement information as well as the company's age and its previous repayment behavior.
	Qualitative Score	Rating score [0; 1] resulting from seven dimensions on the subjective creditworthiness of the customer.
	Individual Score	Subset of the Qualitative Score consisting of the four items on the individual creditworthiness of the customer [0; 1].
	Industry Score	Subset of the Qualitative Score consisting of the three items on the industry outlook of the customer [0; 1].
Ratings	Calculated Rating	Rating result based on Quantitative and Qualitative Score alone.
	Proposed Rating	Rating result based on the Calculated Rating and any overrides by the Loan Officer.
	Approved Rating	Rating result based on the Proposed Rating and any corrections by the Approver. The Approved Rating equals the Proposed Rating for all applications under no-control.
Overrides	$\text{Override}_{\text{LoanOfficer}}$	Difference between the Proposed Rating and the Calculated Rating. Negative values indicate a downgrade by the Loan officer, positive values indicate an upgrade by the Loan Officer. Values of zero indicate no override.
	$\text{Correction}_{\text{Approver}}$	Difference between the Approved Rating and the Proposed Rating. Negative values indicate a downgrade by the Approver, positive values indicate an upgrade by the Approver. Values of zero indicate no correction. Not defined for any applications under no-control.
Influence & Experience	Influence	Dummy variable (0; 1; 2) that takes the value zero if the loan applicants' Quantitative Score is below 0.75, one if the Quantitative Score is above 0.75 and below 0.875 and two if the Quantitative Score is higher than 0.875.
	High Experience	Dummy variable (0;1) taking the value one if the Loan Officer has, at the time of the loan application, above-median experience with the rating tool. Experience is measured as the number of applications completed by a Loan Officer.
	Prev. Corrections	Mean of Corrections by the Approver in all previous applications of a Loan Officer that were controlled by the same Approver. Not defined if the number of interactions between Loan Officer and approver is below 5.
Efficiency	Default	Dummy variable (0;1) taking the value one if the customer defaults within two years following the loan application.
	Application Length	Number of days between the beginning of the rating application and the final approval of the rating result.
Control Variables	Size	Natural logarithm of the balance sheet total (in CHF).
	Industry	Dummy variable, coding the industry of a client into one of 21 categories.

Table 5-2: Summary Statistics of the Sample

The table shows the summary statistics of the variables used throughout the analyses. The variables on Proposed Ratings and Corrections are only defined for controlled applications. Previous Corrections are only available for loan officer with at least 5 rating applications with the same loan officer-approver pairing. Default information is only available for a subset of two banks in our sample.

							Percentiles		
Category	**Variable**	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**	**75%**	**50%**	**25%**
Rating & Control Variables	Control	3'360	0.73	0.44	0	1	1	1	0
	Size	3'360	8.78	0.19	7.74	9.61	8.90	8.80	8.68
Rating Scores	Quantitative Score	3'360	0.78	0.15	0.21	0.97	0.90	0.81	0.68
	Qualitative Score	3'360	0.56	0.14	0.03	1	0.62	0.54	0.49
	Individual Score	3'360	0.54	0.15	0	1	0.55	0.55	0.55
	Industry Score	3'360	0.58	0.20	0	1	0.73	0.53	0.40
Ratings	Calculated Rating	3'360	4.45	1.96	1	8	6	5	3
	Proposed Rating	2'453	4.57	1.88	1	8	6	5	3
	Approved Rating	3'360	4.42	1.84	1	8	6	5	3
Over-rides	Override$_{LoanOfficer}$	3'360	0.07	0.81	-7	6	0	0	0
	Correction$_{Approver}$	2'453	-0.14	0.65	-6	4	0	0	0
Influence & Experience	Influence	3'360	0.96	0.84	0	2	2	1	0
	High Experience	3'360	0.49	0.50	0	1	1	0	0
	Prev. Corrections	1'053	-0.11	0.19	-1.29	0.50	0	0	0
Effi-ciency	Default	1'166	0.073	0.26	0	1	0	0	0
	Application Length	3'360	14.66	56.96	0	1033	7	2	0

Table 5-3: Observations across Banks and Years

The table shows the number of rating applications across banks and years. Banks are coded using letters from A to F. In the last column and in the bottom line, the table shows the share of controlled rating applications across banks and years.

Bank	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**Total**	**Total Relative**	**Share Control**
A		56	144	38	30	6	274	8.2%	**83.9%**
B	203	378	97	99	83	32	892	26.5%	**60.8%**
C		260	141	45	55	28	529	15.7%	**90.9%**
D			13	24	6	40	83	2.5%	**4.8%**
E			61	892	196	50	1,199	35.7%	**99.1%**
F				26	243	114	383	11.4%	**2.1%**
Total	**203**	**694**	**456**	**1,124**	**613**	**270**	**3,360**	**100.0%**	**73.0%**
Share Control	**51.2%**	**78.8%**	**78.1%**	**91.0%**	**52.7%**	**37.0%**	**73.0%**		

5.3. The Credit Rating Process

At the beginning of each rating process, the bank assigns a loan officer to the client. The loan officer is responsible for the interaction with the client and the collection of all required information during the application process. In our setting, banks use a hybrid credit rating model, i.e. it combines hard (quantitative) with soft (qualitative) information. The quantitative part uses information derived from the clients' balance sheet or the financial statement as well as information on a firm's age and its previous repayment history. All quantitative information used in our rating model is both, observable and easily verifiable. Logistic transformation aggregates the quantitative information resulting in the *Quantitative Score* of a client. This score ranges from zero (highest probability of default) to one (lowest probability of default). The qualitative information includes seven questions on different dimensions of the subjective creditworthiness of a client. The questions either target the current condition of the client or prospects of the client's industry and are answered using a categorical assessment, e.g. "above average", "average", or "below average". The aggregation of the subjective assessment yields the *Qualitative Score*, again ranging from zero (highest probability of default) to one (lowest probability of default). Appendix 5-I presents a stylized user interface of the rating model to illustrate this process.

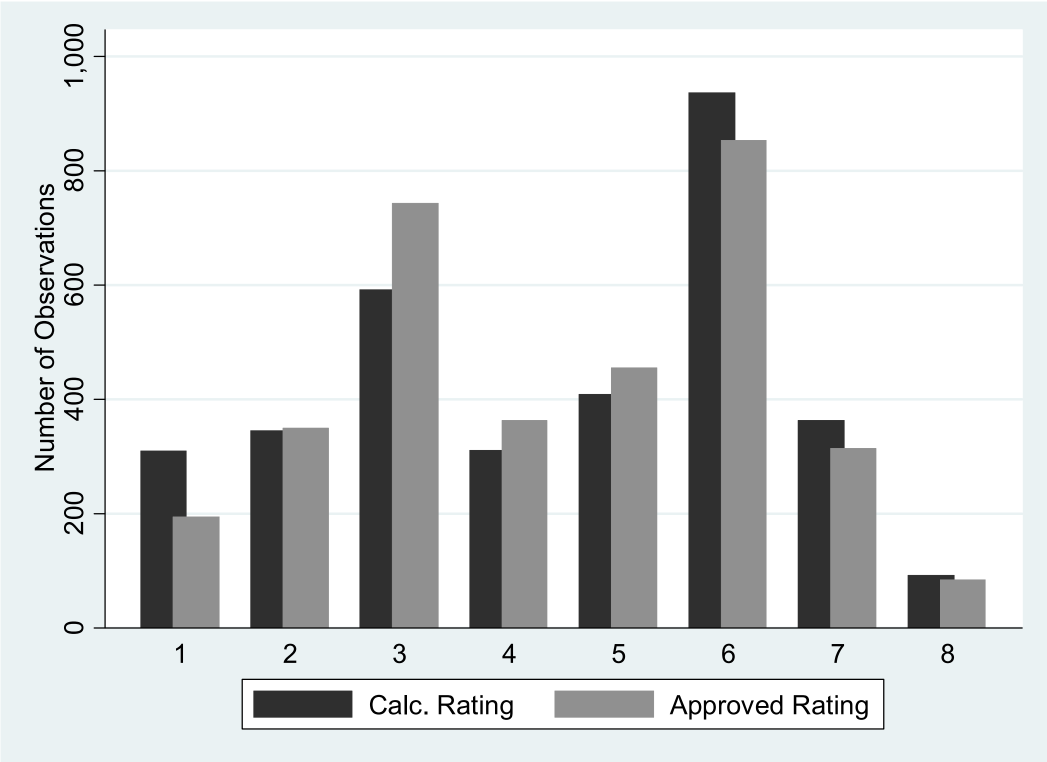
After collecting all necessary information on a client, the credit rating model combines the *Quantitative Score* and the *Qualitative Score* to the *Calculated Rating*. This algorithm non-linearly transforms both metric scores into eight discrete rating classes ranging from 1 (highest probability of default) to 8 (lowest probability of default). The relative weight of both scores only depends on the *Quantitative Score* of a client: For *Quantitative Scores* lower than 0.75, the *Calculated Rating* depends on the *Quantitative Score* of a client alone ("*No Influence*"). It is important to note, that, while the *Qualitative Scores* of customers in this range do not have an influence on the actual rating, the respective information is collected nonetheless. Even more, loan officers receive no formal training on the detailed mechanics of the rating model. Hence, while they are probably able to derive most of the mechanics by repetitively working with the tool, loan officers do not know the exact influence of one score over the other for one particular client. In the next section, for *Quantitative Scores* between 0.75 and 0.875, the influence of the *Qualitative Score* on the *Calculated Rating* increases with higher *Quantitative Scores* of a client ("*Increasing Influence*"). Finally, for *Quantitative Scores* above 0.875, changes in the resulting *Calculated Ratings* are only triggered by the qualitative information of a customer ("*High Influence*"). In this area, the marginal impact of changes in the *Quantitative Score* is hence zero. Appendix 5-II provides a more detailed illustration of the relation between *Quantitative Score*, *Qualitative Score* and *Calculated Rating*, including information on the different rating classes obtainable for a given *Quantitative Score*.

After the calculation of a credit rating, each responsible loan officer has the option to override the *Calculated Rating*. Overrides are possible in both directions, i.e. upgrades and downgrades, and are not restricted in the number of rating notches included. In case a loan officer decides to override a *Calculated Rating,* he/she has to file a report stating the reasons for the override. Basel II restricts the use of overrides of credit rating models to several admissible categories. Admissible are relatively specific reasons as, for example, "technical limitations of the rating tool", but also very general justifications as, for example, "bank-specific reasons". The rating proposed by the loan officer, with or without an override, is the *Proposed Rating*.

After the loan officer proposes a rating for a client, further procedures differ on the organizational design of the loan process: In uncontrolled loan applications, the *Proposed Rating* does not need any further approval. For uncontrolled rating applications, *Proposed Rating* and *Approved Rating* are thus identical. For controlled loan application, this is not the case: After proposing a rating, the loan officer hands the credit file to a second person, the approver. This approver can either be a colleague, a superior, or an employee in an independent business line. The approver reviews the entire application file and then either approves the rating as is or corrects it. If the approver decides to correct the rating, it is in his/her discretion to assign a different rating to the applicant. The approvers' decision is final and the rating after this revision is in any case the *Approved Rating*. To illustrate the potential differences between *Calculated Ratings* and *Approved Ratings,* Figure 5-1 presents the frequency distributions of both ratings across our rating scale.

Figure 5-1: Distribution of Credit Ratings

This figure shows the number of observations in our sample across the different rating classes. Ratings range from 1 (worst) to 8 (best). Distributions are shown for Calculated Ratings and Approved Ratings.



To give an impression on data used in our analyses, in Table 5-4, we present the mean values on several key variables of our empirical analyses, dividing our full sample into observations with and without *Control*. We further include results of t-tests to assess the statistical significance in mean differences. First of all, *Quantitative Scores* of clients in the *Control* and the *No-Control* sample are not statistically different. This is important as controlled and uncontrolled rating applications in our sample mainly stem from different banks. It seems, however, that clients across these subsamples are relatively similar with regard to their objective creditworthiness. *Qualitative Scores* and *Overrides* are significantly different for controlled and uncontrolled rating applications, with more positive *Qualitative Scores* and more positive *Overrides* assigned under *Control*. Mean values of *Calculated* and *Approved Ratings* are then again not statistically different. In line with the previous differences, both figures show higher values for the *Control* subsample. Additionally, average *Default* frequencies are almost identical in both subsamples, the distributions of *Influence*, *Experience*, and *Application Length*, however, are not.

Table 5-4: Differences in Control vs. No-Control Sample

This table presents mean values of several key variables in our empirical analyses. Mean values are presented for the full sample and for Control and No-Control separately. In addition, results of t-Tests between Control and No-Control are presented.

	Mean Values			T-Test	
	Total	No Control	Control	P-Value	Sig.
Size	8.78	8.74	8.80	0.00	***
Quantitative Score	0.78	0.79	0.78	0.10	n.s.
Qualitative Score	0.56	0.51	0.57	0.00	***
Individual Score	0.58	0.51	0.60	0.00	***
Industry Score	0.54	0.51	0.56	0.00	***
Calculated Rating	4.45	4.43	4.46	0.71	n.s.
Approved Rating	4.42	4.40	4.43	0.64	n.s.
$\text{Override}_{\text{LoanOfficer}}$	0.07	-0.04	0.11	0.00	***
Influence	0.97	1.00	0.95	0.10	*
Experience	0.49	0.70	0.42	0.00	***
Default	0.073	0.074	0.073	0.95	n.s.
Application Length	14.66	2.39	19.20	0.00	***

5.4. The Impact of Control on Credit Assessments

5.4.1. The Impact of Control on Proposed Credit Ratings

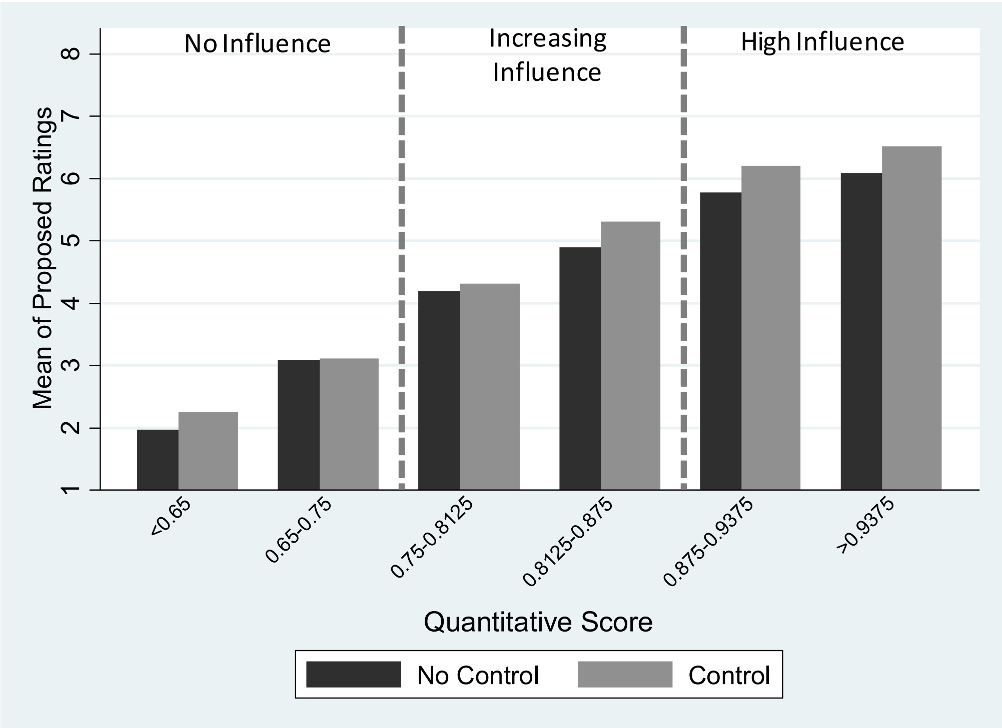
In our empirical section, we test whether loan officers assess their clients differently if the rating is controlled by a second person. In the first step, we allow these differences to be in any part of the rating process that requires the loan officer's discretion, namely the *Qualitative Score* and the *Override*. As an initial assessment, in Figure 5-2 we depict the mean *Proposed Ratings*[22] conditional on each customer being controlled over different classes of *Quantitative Scores*. We pool the *Quantitative Score* into two different buckets within each of the three segments "*No Influence*", "*Increasing Influence*", and "*High Influence*". If control affects the loan officers' behavior, we would expect to find different *Proposed Ratings* for clients with similar quantitative information if the client's rating is controlled. Figure 5-2 shows that *Proposed Ratings* under *Control* are consistently higher (better) across all *Quantitative Scores*. The figure further shows that these differences increase with higher

[22] In all analyses, the *Proposed Rating* for observations without control equal the *Approved Rating* of the client.

Quantitative Scores. The visual analysis hence indicates that the loan officers' assessment of a rating applicant is more positive if the loan officer anticipates the rating to be controlled by a second person.

Figure 5-2: The Impact of Control on Proposed Ratings

This figure shows the mean Proposed Ratings under control and under no-control. Observations are clustered across different quantitative scores. Vertical lines identify the areas with differing influence of the Qualitative Score on the Calculated Rating.



In Table 5-5, we extend this analysis to a multivariate OLS-regression. We use the *Proposed Rating* as dependent variable and a dummy variable on *Control* as the independent variable of interest. We include the *Quantitative Score* of each client to control for any systematic differences in the use of *Discretion* of objectively good and objectively bad clients. We control for the *Size* of a client, measured as the natural logarithm of the balance sheet total, and we include industry fixed effects as the rating tool's accuracy might be different along both dimensions. We also include year fixed effects to control for any unobservable heterogeneity over time. As we expect systematic differences in the use of *Discretion* for different loan officers, we cluster standard errors on the loan-officer level.

Table 5-5: Impact of Control on Proposed Rating

This table presents linear estimation results for the impact of Control on Propsed Ratings. Standard errors are clustered on the loan officer level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. Column (1) presents our baseline regression including all available observations. Columns (2) to (4) show the results for three subsamples depending on the impact of the Qualitative Score on the Calculated Rating. Columns (5) to (7) present additional robustness tests. In column (5), we repeat the analysis for the one bank that uses both, control and no-control to similar degrees (Bank B). Column (6) excludes all control observations from banks that mainly employ no-control and all no-control observations from banks that mainly employ control in their credit assessments. Column (7) includes only observations that are initiated at least one year after the rating tool was introduced at the respective bank. See Table 1 for detailed definitions on all variables.

	Coefficient (Std. Error)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent	**All**	**No Influence**	**Increasing Influence**	**High Influence**	**Mixed Bank**	**Control / No Control / Mixed**	**Rating Model in Use > 1yr**
Control	0.192***	0.0785	0.232**	0.303***	0.187	0.177***	0.196***
	[0.0628]	*[0.0663]*	*[0.0897]*	*[0.0868]*	*[0.118]*	*[0.0659]*	*[0.0699]*
Quant. Score	10.22***	4.516***	18.85***	6.329***	8.785***	10.23***	9.986***
	[0.210]	*[0.314]*	*[0.707]*	*[1.059]*	*[0.318]*	*[0.217]*	*[0.306]*
Size	0.784***	0.435***	0.282*	1.390***	0.802***	0.825***	0.631***
	[0.114]	*[0.132]*	*[0.144]*	*[0.221]*	*[0.242]*	*[0.117]*	*[0.152]*
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.726	0.256	0.475	0.175	0.644	0.721	0.720
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	3,360	1,248	983	1,129	892	3,245	1,360

Our results in Table 5-5 indicate that loan officers propose significantly higher ratings for their customers if the rating is controlled by a second person. In our full sample, the estimation results in column (1) show a statistically significant impact of *Control* amounting to 0.192*** rating steps. Across all observations, roughly one in five clients, whose rating is controlled, receives a *Proposed Rating* that is one notch higher. Taking the total range of rating classes, one to eight, into account, these results are also economically relevant. In columns (2) to (4), we repeat our analysis for customers with varying *Quantitative Scores.* We find an increasing impact of *Control* for (observably) more creditworthy clients. For the subsample with *No Influence* of *Qualitative Score*s on *Calculated Ratings*, we find no statistically robust impact at a distinctively lower, yet positive point estimate of 0.0785. In the mid-section, *Increasing Influence*, the results are almost identical to the full sample with 0.232** steps higher *Proposed Ratings* under *Control*. This value increases to 0.303*** rating steps for the subsample with *High Influence*.[23] The differences among these subsamples could be attributed to two different effects: First, the loan officers' assessment of clients might be more positive under *Control* if the client shows a higher (observable) creditworthiness. Second, assuming a constant effect of *Control* on both, qualitative assessment and *Overrides*, the increasing impact of *Control* could also be the technical result of the increasing relevance of subjective information with increasing *Quantitative Scores*. We will disentangle these explanations in the following sections.

In columns (5) to (7), we add additional robustness tests to our main results. In column (5), we restrict the analysis to the one bank in our sample that uses *Control* and *No-Control* almost evenly (Bank B, Share of *Control*: 60.8%). Since our total sample mostly consists of banks that either use *Control* or *No-Control* almost exclusively, our findings might be driven by differences in the banks rather than the mere existence of *Control*. While the results in column (5) lack statistical significance, the point estimate is virtually identical to the full sample (0.187) indicating that it is in fact *Control* that drives our results. In column (6), we use information on all banks in

[23] In unreported analyses, we test the statistical significance for the different point estimates of the three subsamples using interactions terms of (*Control * Increasing Influence*) and (*Control * High Influence*). The estimated coefficient (standard error) for the *Increasing Influence* subsample is 0.108 (0.117) and 0.346*** (0.106) for the *High Influence.*

our sample but exclude any observations that do not match the main pattern of a bank with regard to controlling rating applications. We exclude any controlled observations of banks that usually do not control their loan officers (Banks D and F) and we exclude all observations without *Control* at banks that usually control their loan officers (Banks A, C, and E). We use this test to gain confidence that the impact of control on the *Proposed Ratings* is not driven by these exceptional cases. The results in column (6) remain qualitatively unchanged. In column (7), we add a specification that only includes observations that were initiated at least one year after the rating tool was introduced at the respective bank. This analysis was included as it might be the case that, early after the adoption of a new rating tool, loan officers might feel unfamiliar with it and behave systematically different during this period. Results show, however, that the impact of *Control* is not triggered by the introduction of the rating tool.

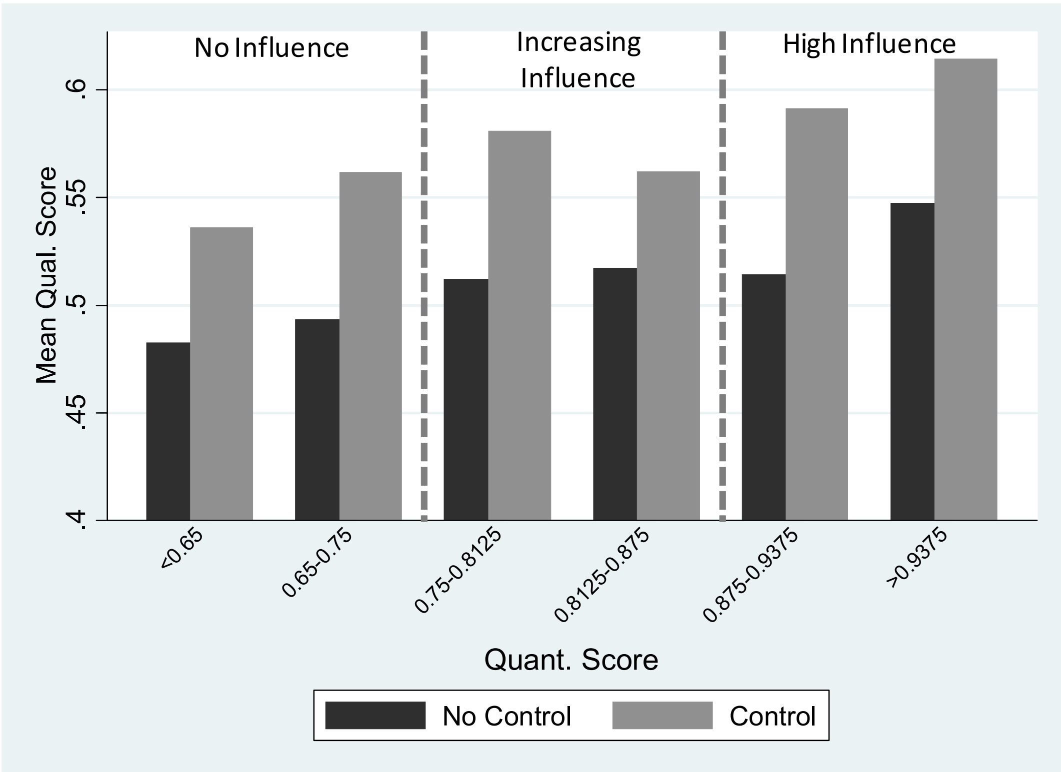
5.4.2. The Impact of Control on Qualitative Assessments

Overall, loan officers assign significantly higher credit ratings to their clients if the loan officers' assessment is controlled by a second person. In the following two sections, we analyze which part of the rating process triggers these differences. Following the design of the rating process, loan officers use their discretion at two different steps: The qualitative assessment of a customer and the *Override* of the customer's *Calculated Rating*. Focusing on the differences in the qualitative assessment of customers, Figure 5-3, Panel A presents the mean *Qualitative Scores* over the identical clusters of *Quantitative Scores* as in the Figure 5-2. In line with our previous finding, Figure 5-3, Panel A also shows consistently higher qualitative assessments for clients whose credit rating is controlled by a second person. With these higher *Qualitative Scores* in mind, in Figure 5-3, Panel B we extent this analysis to the question if the observed differences in the qualitative assessment also result in different rating results. We plot the customers' average *Calculated Rating*, i.e. the rating that solely depends on quantitative and qualitative information of a client, over different buckets of *Quantitative Scores*. In the *No Influence* subsection, we find no differences between observations under *Control* and under *No-Control*. This observation indicates that any differences in controlled and uncontrolled subsamples are not driven by systematic variations in the composition of both samples. In line with previous results, we find increasingly higher *Calculated Ratings* for controlled rating applications in the subsections with *Increasing Influence* and *High Influence*. The observed differences in the qualitative assessment of customers carry over to higher *Calculated Ratings* whenever the mechanics of the rating model allow this transition.

Figure 5-3: The Impact of Control on the Qualitative Assessment

Panel A: Differences in Qualitative Scores between Control and No-Control

This panel illustrates the differences in the qualitative assessment of clients depending on Control. The figure plots the mean of Qualitative Scores across different classes of Quantitative Scores. Vertical lines identify areas with differing influence of the Qualitative Score on the Calculated Rating.



Panel B: Differences in Calculated Ratings between Control and No-Control

This panel presents the differences in Calculated Ratings resulting from different qualitative assessments of clients. The figure plots the mean of Calculated Ratings across different classes of Quantitative Scores.

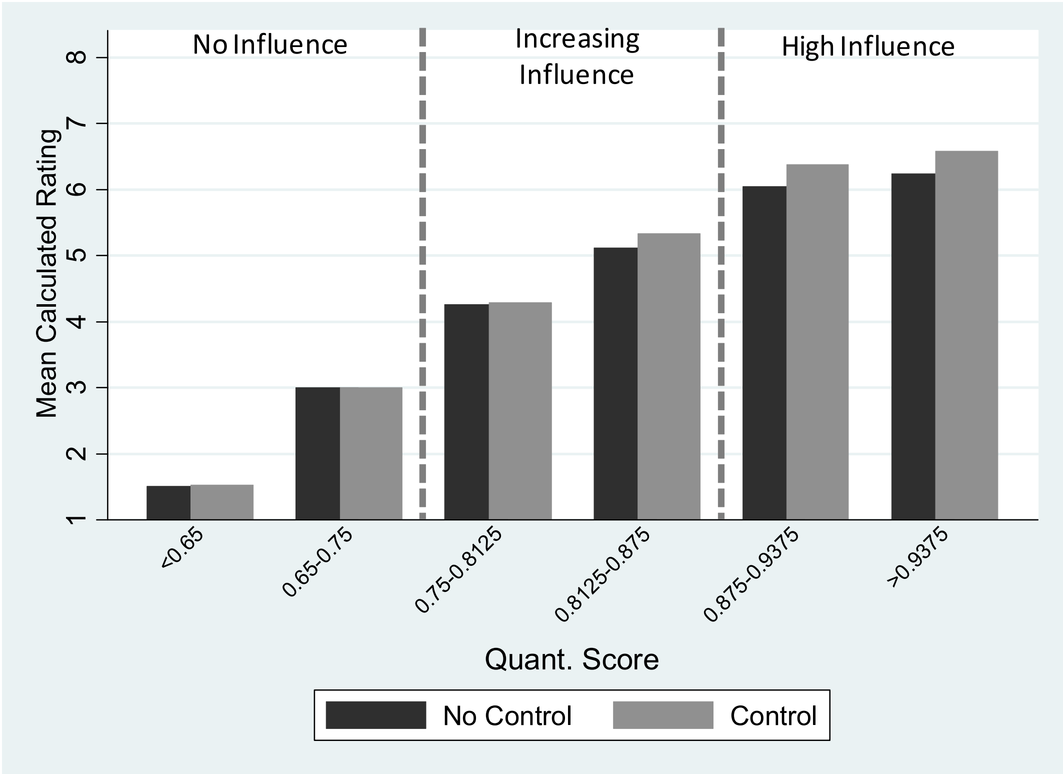


Table 5-6 confirms the findings that loan officers assign higher *Qualitative Scores* under *Control* and that these higher scores translate into higher *Calculated Ratings*. In Table 5-6, Panel A, we linearly regress our dummy variable *Control* on the *Qualitative Score* of a customer. We include identical control variables and fixed effects as in our baseline regression in Table 5-5. Column (1) presents estimation results for all observations in our sample. In accordance to the results in Figure 5-3, we find that *Qualitative Scores* are, on average, 0.0485*** units higher if a rating applications is controlled by a second person. Subsample analyses in columns (2) to (4) further also confirm the impression that these differences remain at constant levels across customers with any *Quantitative Scores*.[24]

[24] Unreported robustness tests confirm the statistical insignificance of differences in point estimates for the three subsamples. Interacting *Control* with *Increasing Influence* yields a coefficient (standard error) of -0.00231 (0.0113), the interaction of *Control* with *High Influence* results in a estimation coefficient (standard error) of 0.0165 (0.0168).

In columns (5) and (6), we add two additional specifications on two subcomponents of the *Qualitative Score*. We divide the seven questions that make up the *Qualitative Score* into three questions that aim to assess the current and prospective state of the customer's industry (*Industry Score*) and four questions on the subjective creditworthiness of the client itself (*Individual Score*). This approach is motivated by two aspects: First, loan officers might have different abilities in assessing both of these components. This notion is supported by the summary statistics of the variables in Table 5-2 that indicate different variations in values for both scores. Loan officers show hardly any variation in the assessment of the *Individual Score* of a customer, whereas the *Industry Score* shows distinctively more variation. Second, if loan officers intend to manipulate the rating outcome in anticipation of being controlled, they might manipulate the *Individual Score* of a customer as the validity of this score is almost impossible to verify. *Industry Scores*, in contrast, could be easily verified using cross-comparisons with clients of the same industry. In line with this second argument, the estimation results in column (5) and column (6) show a stronger impact of *Control* on the *Individual Score* (0.0651***) as on the *Industry Score* (0.0373***).

Our estimation results in Table 5-6, Panel B, confirm our findings that the better qualitative assessment of customers under *Control* also results in higher *Calculated Ratings*. Using identical input parameters as in our previous analyses and the *Calculated Rating* as dependent variable, we find that, across all observations, *Calculated Ratings* are 0.0809** rating steps higher if a rating application is controlled by a second person. This total effect translates into insignificant differences (-0.0413) in the subsample with lowest *Quantitative Scores* and increasing differences for the subsamples with *Increasing Influence* (0.0853**) and *High Influence* (0.229***).[25]

[25] Unreported robustness tests show that these differences are also statistically significant. Interaction terms between *Control* and *Increasing Influence* and *High Influence* yield coefficients (standard errors) of 0.143*** (0.0518) and 0.400*** (0.0581), respectively.

Table 5-6: The Impact of Control on the Qualitative Score

This table presents estimation results on the impact of Control on Qualitative Scores and resulting Calculated Ratings. All estimations employ linear regression and cluster standard errors on the Loan-Officer level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Table 5-1 for definitions on all variables.

Panel A: Qualitative Score as Dependent Variable

Panel A presents the estimation results with the Qualitative Score as dependent variable. Column (1) presents our baseline regression including all available observations. Columns (2) to (4) split the sample according to the influence of the Qualitative Score on the Calculated Rating. Column (5) shows the estimation result for the questions of the Qualitative Score that focus on the industry of the client. Column (6) presents the results for all questions of the qualitative assessment that target the client itself.

Dependent:	**Qualitative Score**				**Industry Score**	**Individual Score**
	Coefficient (Std. Error)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Independent	**All**	**No Influence**	**Increasing Influence**	**High Influence**	**All**	**All**
Quant. Score	0.149***	0.169***	-0.0597	0.690***	0.153***	0.142***
	[0.0186]	*[0.0377]*	*[0.128]*	*[0.139]*	*[0.0225]*	*[0.0265]*
Control	0.0485***	0.0501***	0.0422***	0.0519***	0.0373***	0.0651***
	[0.0126]	*[0.0141]*	*[0.0162]*	*[0.0157]*	*[0.0131]*	*[0.0156]*
Size	0.124***	0.107***	0.117***	0.190***	0.122***	0.126***
	[0.0146]	*[0.0202]*	*[0.0262]*	*[0.0243]*	*[0.0156]*	*[0.0226]*
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.145	0.141	0.114	0.190	0.103	0.100
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	3,360	1,248	983	1,129	3,360	3,360

Panel B: Calculated Rating as Dependent Variable

This panel presents the estimation results with the Calculated Rating as dependent variable. Column (1) includes all observations. Columns (2) to (4) split the sample based on the impact of the Qualitative Score on the Calculated Rating.

Dependent:	**Calculated Rating**			
	Coefficient (Std. Error)			
	(1)	**(2)**	**(3)**	**(4)**
Independent	**All**	**No Influence**	**Increasing Influence**	**High Influence**
Quant. Score	12.16***	6.718***	21.33***	3.781***
	[0.154]	*[0.146]*	*[0.435]*	*[0.794]*
Control	0.0809**	-0.0413	0.0853**	0.229***
	[0.0389]	*[0.0278]*	*[0.0425]*	*[0.0563]*
Size	0.500***	-0.0114	0.290***	0.931***
	[0.0877]	*[0.0579]*	*[0.0933]*	*[0.132]*
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS
R-squared	0.882	0.820	0.775	0.163
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	3,360	1,248	983	1,129

5.4.3. The Impact of Control on Overrides

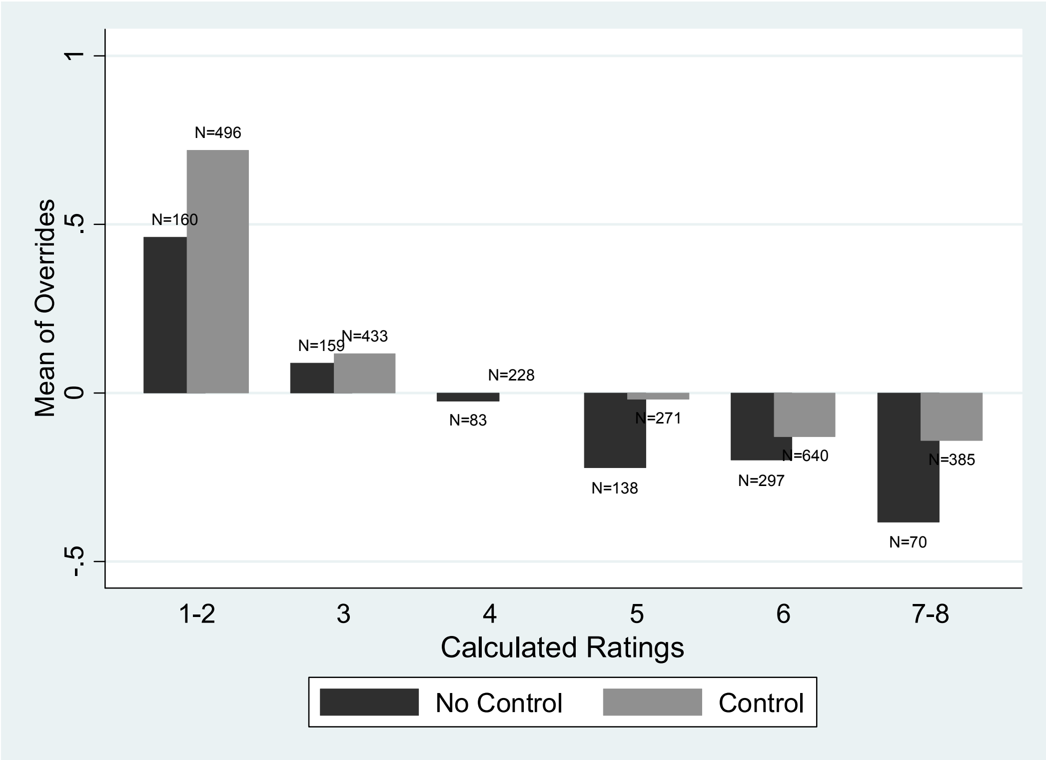
In this section, we focus on the loan officers' second possibility to actively influence the rating result: *Overrides* of *Calculated Ratings*. In Figure 5-4, we plot the mean of *Overrides* by loan officers against different *Calculated Ratings*. We divide the observations by *Control* and combine the highest and the lowest two rating classes, respectively, to keep the number of available observations at comparable levels. Irrespective of the impact of *Control*, the general trend shows positive *Overrides* for low *Calculated Ratings* and negative *Overrides* for high *Calculated Ratings*. Overall, loan officers have a tendency to use *Overrides* in order to push ratings in the medium ranges. Focusing on the impact of *Control*, we find that *Overrides* are consistently more positive if a second person needs to approve a rating: For low *Calculated Ratings*, *Overrides* are more positive under *Control*, for high *Calculated Ratings*, *Overrides* are less negative under *Control*.

Linear regression results in Table 5-7 confirm these findings that loan officers assign more positive *Overrides* under *Control*. We use identical input parameters as in the previous analysis, but replace the *Quantitative Score* as a control variable with fixed effects on the *Calculated Ratings* as these fixed effects enable us to capture the non-linear trend in overriding behavior across rating classes. As a dependent variable, we use the *Override* by the loan officer. Estimation results for our full sample are summarized in column (1). The results show that the loan officers' *Overrides* are, on average, 0.113* rating steps higher if a rating application is controlled by a second person. While statistical significance varies, subsample analyses on the different influence-areas in columns (2) to (4) suggest that this effect is relatively constant across clients with different *Quantitative Scores* (*No Influence*: 0.106; *Increasing Influence*: 0.154*; *High Influence*: 0.0984).[26]

[26] The interpretation of constant coefficients across subsamples is confirmed by unreported tests using interaction terms of *Control* with *Increasing Influence* and *High Influence*. The resulting estimated coefficients (standard errors) are -0.0115 (0.110) for *Increasing Influence* and -0.00681 (0.104) for *High Influence*.

Figure 5-4: The Impact of Control on Overrides

This figure plots the average Override depending on the Calculated Rating of a client. The lowest and highest two rating classes are aggregated to keep the number of observations within the different categories similar. On top of each bar, the number of observations is displayed.



Taken together, we find that, contrary to recent literature in banking research, loan officer are not more conservative if they are under *Control*. We find that loan officer assign higher *Qualitative Scores* and more positive *Overrides* if they are controlled by a second person. We further find that loan officers manipulate that part of the *Qualitative Score* the most that is, supposedly, the least verifiable. The difference in the subjective assessment of clients also translates into significantly higher *Proposed Ratings* under *Control*. The impact of *Control* does not focus on exceptionally good or exceptionally bad clients based on the observable creditworthiness.

Table 5-7: The Impact of Control on Overrides by Loan Officers

This table presents linear estimation results with the Overrides by Loan Officers as dependent variable. For all analyses, standard errors are clustered on the Loan-Officer level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. Column (1) presents estimation results for all observations. Columns (2) to (4) split the sample based on the different impact of the Qualitative Score on the Calculated Rating. See Table 5-1 for definitions on all variables.

Dependent:	**Override$_{LoanOfficer}$**			
	Coefficient (Std. Error)			
	(1)	**(2)**	**(3)**	**(4)**
Independent	**All**	**No Influence**	**Increasing Influence**	**High Influence**
Control	0.113*	0.106	0.154*	0.0984
	[0.0587]	*[0.0665]*	*[0.0887]*	*[0.0791]*
Size	0.342***	0.439***	-0.00606	0.460***
	[0.0871]	*[0.126]*	*[0.104]*	*[0.163]*
Industry FE	Yes	Yes	Yes	Yes
Calc. Rating FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS
R-squared	0.177	0.150	0.051	0.068
Clustered Standard Errors	LO	LO	LO	LO
# Rating Applications	3,360	1,248	983	1,129

5.5. Corrections by Approvers

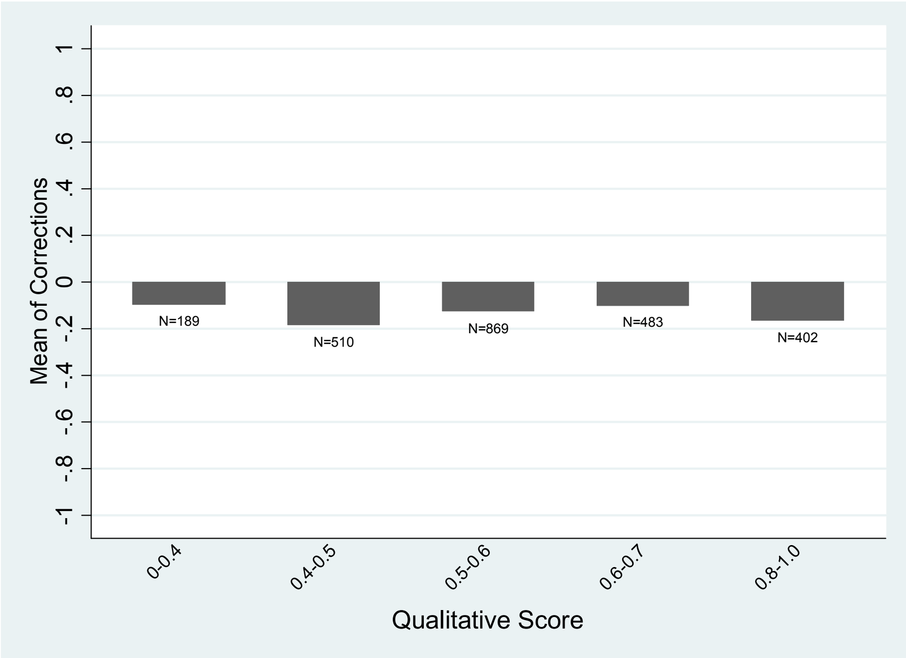
5.5.1. Do Approvers Correct the Loan Officers' Assessment?

If loan officers use their discretion to assign better ratings to customers whenever these ratings need to be approved by a second person, do the approvers realize this bias and react accordingly? In Figure 5-5, we plot the mean of the *Corrections* by the approver over different clusters of the *Qualitative Scores* assigned by the loan officer (Panel A) and the *Overrides* assigned by the loan officer (Panel B). The results in Panel A show that, while the approvers' *Corrections* tend to be negative on average, there are no systematically different responses to different qualitative assessments. This picture completely reverses for Panel B. While overall levels of *Corrections* are still mostly negative, more positive *Overrides* by a loan officer trigger distinctively stronger and more negative responses of the approvers.

Figure 5-5: Corrections by the Approvers

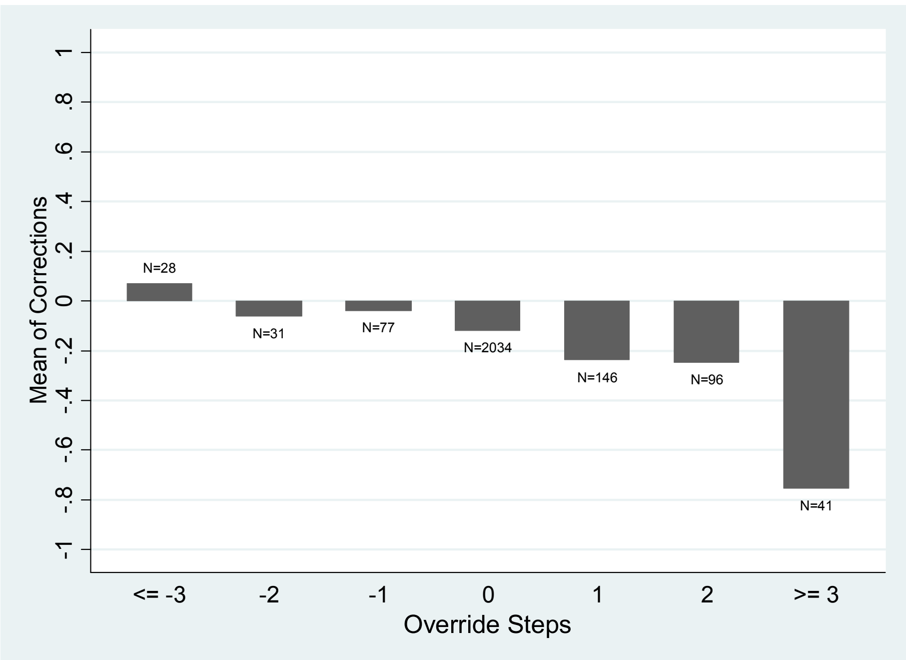
Panel A: Corrections Depending on the Qualitative Assessment

This figure plots the mean of the corrections by the Approver depending on the qualitative assessment of the Loan Officer. At the bottom of each bar, the number of available observations is displayed.



Panel B: Corrections Depending on the Overrides by Loan Officers

This figure plots the mean of the corrections by the Approver depending on the Override by the Loan Officer. Overrides larger than +/- 3 rating steps are clustered into one category each. Outside of each bar, the number of available observations in this category is displayed.



Linear estimation results in Table 5-8 confirm the finding that *Corrections* by approvers are strongly tied to *Overrides* but not to the *Qualitative Score* of a customer. All specifications in Table 5-8 restrict the analysis to the subsample of controlled observations. We use the *Correction* by the approver as the dependent variable while controlling for *Size* and including fixed effects on *Industries*, *Years*, and *Calculated Ratings*. All standard errors are again clustered on the loan officer-level. Columns (1) to (4) further include the *Qualitative Score* as independent variable. Columns (5) to (8) include the *Overrides* of the loan officers.

The results summarized in columns (1) to (4) show no statistically significant impact of the qualitative assessment on the approvers' *Corrections*. For the full sample of controlled observations (column 1), the point estimate is essentially zero and statistically insignificant (0.0174). While estimation results increase for observations with increasing importance of the *Qualitative Score* on *Calculated Ratings* (*No Influence*: 0.0226; *Increasing Influence*: 0.249; *High Influence*: 0.216), results are consistently insignificant.[27] If anything, the estimated coefficients indicate that better *Qualitative Scores* correlate with positive *Corrections* by approvers rather than triggering a reaction the other way around.

The results in columns (5) to (8), however, provide evidence that approvers tend to reverse *Overrides* by loan officers. The point estimate on the full sample of controlled applications in column (5) suggests that approvers reverse roughly one out of five *Overrides* by the loan officer (-0.170***). This effect slightly decreases with an increasing observable creditworthiness of the customer (columns 6 to 8). For the *No Influence* subsample, the approvers' *Corrections* most strongly depend on previous *Overrides* by the loan officer (-0.194***). For *Increasing Influence* and *High Influence*, the value decreases to -0.160*** and -0.130***, respectively.[28]

[27] In line with the insignificant results in all subsamples, we also find no statistical difference between the samples. Using an interaction of the *Qualitative Score* with *Increasing Influence* and with *High Influence*, we find estimated coefficients (standard errors) of 0.126 (0.324) and 0.356 (0.377), respectively.

[28] The differences between estimated coefficients are qualitatively confirmed in additional unreported tests, but are not statistically significant. Corresponding analyses with an interaction term of the *Override* by a loan officer with *Increasing Influence* or *High Influence*, yields coefficients (standard errors) of 0.0286 (0.0592) and 0.0790 (0.0501), respectively.

Table 5-8: Corrections by the Approvers

This table presents linear estimation results with the Corrections by the Approver as dependent variable. All standard errors are clustered on the Loan-Officer level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. Columns (1) and (5) present estimation results for the full sample of controlled applications. Columns (2) to (4) and (6) to (8) each present the results for subsamples with a different impact of the Qualitative Score on the Calculated Rating. See Table 5-1 for definitions on all variables.

Dependent: Correction$_{Approver}$

	Coefficient (Std. Error)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent	**All**	**No Influence**	**Increasing Influence**	**High Influence**	**All**	**No Influence**	**Increasing Influence**	**High Influence**
Qual. Score	0.0174	0.0226	0.249	0.216				
	[0.142]	*[0.180]*	*[0.260]*	*[0.421]*				
Override$_{LoanOfficer}$					-0.170***	-0.194***	-0.160***	-0.130***
					[0.0265]	*[0.0369]*	*[0.0462]*	*[0.0386]*
Size	-0.0132	-0.249*	-0.0801	0.612***	0.0630	-0.129	-0.0587	0.691***
	[0.0881]	*[0.127]*	*[0.133]*	*[0.206]*	*[0.0850]*	*[0.112]*	*[0.141]*	*[0.207]*
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calc. Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.029	0.074	0.045	0.050	0.067	0.169	0.060	0.064
Clustered Standard Errors	LO	LO	LO	LO	LO	LO	LO	LO
# Rating Applications	2,453	929	718	806	2,453	929	718	806

5.5.2. Do Loan Officers Anticipate Corrections?

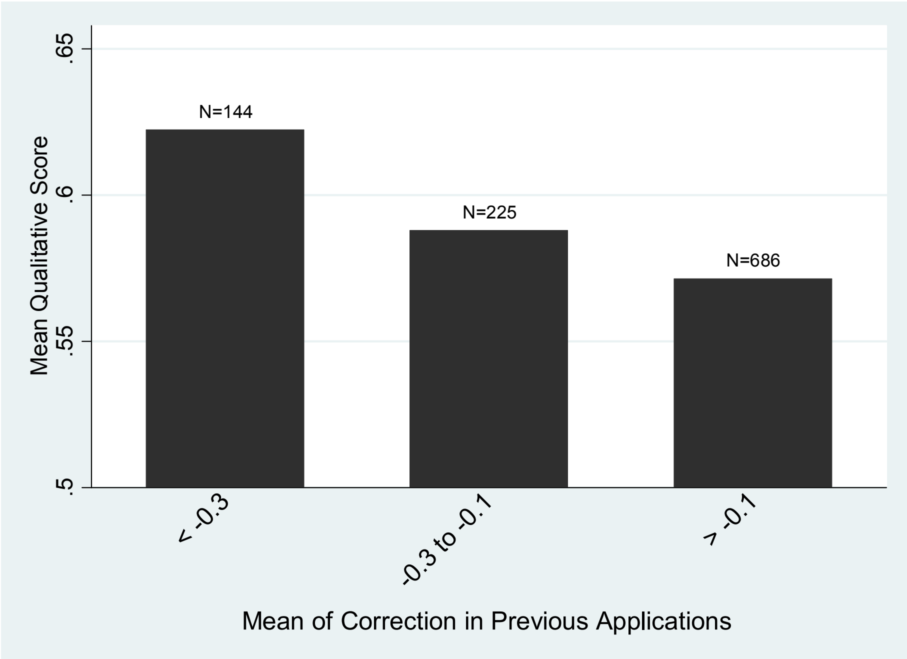
Our previous findings show that approvers react on the easily observable use of discretion by loan officers. This raises the question if the same is true the other way around – that is, whether loan officers learn from previous experience with the approvers. To answer this question, in Figure 5-6, we plot the mean *Qualitative Score* assigned by loan officers (Panel A) and the mean of the *Overrides* by loan officers (Panel B) against the average *Previous Corrections* in rating applications prior to the current application. Previous applications are defined as any rating applications of a loan officer that were corrected by the same approver as the current application. As we suspect the use of discretion to systematically vary among loan officers, we expect the correcting behavior of approvers to vary accordingly. If this is the case, we argue that, if anything, loan officers should learn from their experience with specific approvers and adjust their behavior accordingly. We restrict the calculation of *Previous Corrections* to credit applications where loan officer and approver are paired at least for the fifth time. We use this restriction to make sure that loan officers actually had the opportunity to get to know the approver's behavior. Panel A and Panel B of Figure 5-6 show that loan officers assign higher *Qualitative Scores* and more positive *Overrides* in response to a higher a share of negative *Corrections* in previous rating applications.

Linear regression results in Table 5-9 confirm the impression that loan officers adjust their use of discretion on the basis of their previous experience with an approver. We use *Previous Corrections* as the independent variable of interest. As in the previous analyses, we include *Size* as control variable and fixed effects on *Industries*, *Years*, and *Calculated Ratings*. We further cluster all standard errors on the loan officer-level. Columns (1) to (4) summarize results of regressions on the *Qualitative Score,* columns (5) to (8) the results on the *Overrides* by loan officers.

Figure 5-6: The Loan Officers' Reaction on Previous Corrections

This figure illustrates the impact of previous corrections by the Approver on the behavior of the Loan Officer. A negative mean of Corrections in previous assessments indicates that the Approver, on average, downgraded the rating proposed by the Loan Officer. As Corrections are mostly negative, we do not present an additional cluster with, on average, positive Corrections. On top of each bar, the number of available observations is displayed.

Panel A: The Impact of Previous Corrections on the Qualitative Assessment



Panel B: The Impact of Previous Corrections on the Overrides

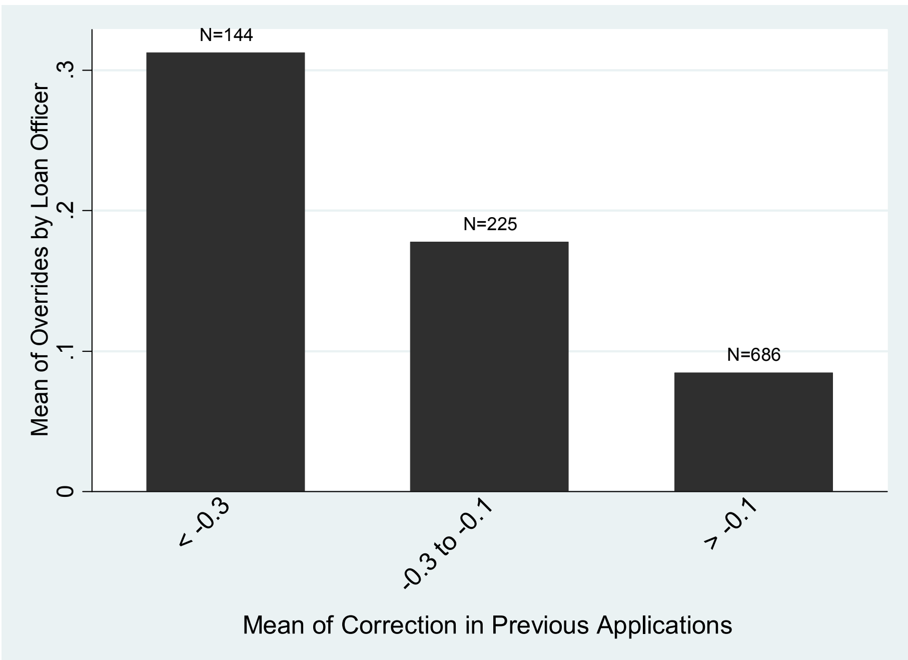


Table 5-9: Loan Officers' Reactions on Previous Corrections

This table presents linear estimation results for the Loan Officers' behavior depending on the frequency of Corrections in previous assessments. For columns (1) to (4), the dependent variable is the Qualitative Score of a client. For columns (5) to (8), the dependent variable is the Override by the Loan Officer. Additionally, columns (2) to (4) and (6) to (8) present different subsamples for varying degrees of the influence of the qualitative assessment on the calculated rating. All standard errors are clustered on the loan officer-level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Table 5-1 for definitions on all variables.

Dependent:	**Qualitative Score**				**Override$_{LoanOfficer}$**			
	Coefficient (Std. Error)							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Independent	**All**	**No Influence**	**Increasing Influence**	**High Influence**	**All**	**No Influence**	**Increasing Influence**	**High Influence**
Prev. Corrections	-0.0494*	-0.0296	-0.148**	-0.0141	-0.384***	-0.547*	-0.455**	-0.195
	[0.0296]	*[0.0398]*	*[0.0610]*	*[0.0145]*	*[0.121]*	*[0.281]*	*[0.175]*	*[0.183]*
Size	0.111***	0.120***	0.0891	0.0249	0.365**	0.471*	-0.210	0.397
	[0.0256]	*[0.0421]*	*[0.0569]*	*[0.0172]*	*[0.141]*	*[0.239]*	*[0.146]*	*[0.249]*
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calc. Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.339	0.123	0.276	0.830	0.209	0.204	0.082	0.081
Clustered Standard Errors	LO	LO	LO	LO	LO	LO	LO	LO
# Rating Applications	1,055	399	283	373	1,055	399	283	373

We find that, loan officers assign higher *Qualitative Scores* the more their ratings were corrected by the approver in previous applications. For all available observations in column (1), we find that an average downward correction by one rating step increases the *Qualitative Score* assigned in subsequent applications by roughly five percentage point (-0.0494*). In column (2) we find no impact of *Previous Corrections* on the *Qualitative Score* if the *Qualitative Score* does not have an impact on the *Calculated Rating* (-0.0296). In the mid-section of *Quantitative Scores* (column 3), we find that the loan officer's sensitivity to *Previous Corrections* is largest and also statistically significant (-0.148**). For customers with very high *Quantitative Scores* (column 4), we find no impact of *Previous Corrections* on the *Qualitative Score* (-0.0141).[29] Overall, the results suggest that the loan officers' assessments specifically aim at anticipating corrections of the approvers. Hence, loan officers only use the *Qualitative Score* to manipulate a rating, when the mechanics of the rating tool allow

[29] These results are confirmed by additional tests using an interaction term on *Previous Corrections* and *Increasing Influence* or *High Influence*. For *Increasing Influence*, the estimated coefficient (standard error) is -0.144** (0.0640). For *High Influence*, the estimated coefficient (standard error) amounts to -0.0153 (0.0189).

them to (column 2 vs. 3) and where a correction by the approver is more likely, i.e. the mid-section of *Quantitative Scores*.

When looking at the *Overrides* as a response to *Previous Corrections*, we also find that loan officers learn fromprevious *Corrections* and adjust their *Override* behavior accordingly. For all available observations in column (1), we find that roughly one *Correction* every three rating applications is sufficient to trigger an additional *Override* in the opposite direction (-0.384***) for subsequent rating applications. While we still find no such relation for the subsample with highest *Quantitative Scores* (column 8: -0.195), these values even increase to -0.547* and -0.455** when looking at the subsamples in the low (column 6) and mid-section (column 7) of *Quantitative Scores*.[30]

5.6. The Importance of Loan Officers' Experience

The previous section shows that loan officers learn from their experience with an approver, i.e. loan officers increase their use of discretion in response to frequent corrections in previous applications. Building on these observations, we generally expect more experienced loan officers to make a more nuanced use of their discretion when being controlled. We define experience as a loan officer-specific measure based on the number of previous rating applications a loan officer completed prior the current observation. We define a *High Experience* (*Low Experience*) loan officer as one who completed more (less) rating applications than the median in our total sample (13). To test if there are in fact differences, we repeat our previous analyses splitting our sample into *High Experience* and *Low Experience* loan officers in Table 5-10. Other than the median-split along loan officer experience and the dependent variable, all specifications are identical to our baseline regression in Table 5-5. Column (1) and (2) present the estimation results for the *Proposed Rating* as dependent variable, columns (3) and (4) use the *Qualitative Score*, columns (5) to (6) and (7) to (8) use the *Industry Score* and the *Individual Score*, respectively. In columns (9) and (10), we use the *Calculated Rating* as dependent variable.

[30] Results on the significance in differences across subsamples confirm that the effect is strongest for the *Increasing Influence* subsample. Between *No Influence* and *High Influence*, however, we find no significant differences. Using interaction terms on *Previous Corrections* and *Increasing Influence* or *High Influence*, we find estimation coefficients (standard errors) of -0.309* (0.161) and -0.0658 (0.183), respectively.

Table 5-10: Relevance of Loan Officers' Experience

This table shows how the experience of loan officers influences their behavior in the credit assessment under control and no-control. Standard errors are clustered on the loan officer level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Table 5-1 for detailed definitions on all variables.

Panel A: Qualitative Assessment

Columns (1) and (2) use the Proposed Rating as dependent variable, columns (3) and (4), (5) and (6), (7) and (8), and (9) and (10) use the Qualitative Score, the Industry Score, the Individual Score, and the Calculated Rating, respectively. Additionally, odd columns present results for loan officers with Low Experience, while even columns show results for highly experienced loan officers.

Dependent:	**Proposed Rating**		**Qualitative Score**		**Industry Score**		**Individual Score**		**Calculated Rating**	
	Coefficient (Std. Error)									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Independent	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**
Control	0.104	0.205***	0.0179	0.0601***	0.0172	0.0394**	0.0190	0.0903***	-0.0162	0.123**
	[0.0958]	*[0.0766]*	*[0.0126]*	*[0.0160]*	*[0.0128]*	*[0.0156]*	*[0.0179]*	*[0.0236]*	*[0.0505]*	*[0.0505]*
Quantitative Score	10.37***	10.03***	0.186***	0.114***	0.192***	0.115***	0.177***	0.112***	12.48***	11.83***
	[0.228]	*[0.299]*	*[0.0246]*	*[0.0251]*	*[0.0284]*	*[0.0295]*	*[0.0335]*	*[0.0370]*	*[0.182]*	*[0.200]*
Size	0.759***	0.780***	0.139***	0.106***	0.129***	0.111***	0.152***	0.0987***	0.483***	0.499***
	[0.144]	*[0.173]*	*[0.0213]*	*[0.0196]*	*[0.0220]*	*[0.0216]*	*[0.0333]*	*[0.0295]*	*[0.116]*	*[0.113]*
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
R-squared	0.734	0.723	0.156	0.168	0.128	0.108	0.107	0.131	0.885	0.883
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	1,702	1,658	1,702	1,658	1,702	1,658	1,702	1,658	1,702	1,658

Panel B: Overrides

This table presents linear estimation results with the Override of the loan officer as dependent variable. Columns (1) and (3) present estimation results for Low Experience loan officers, columns (2) and (4) present estimation results for High Experience loan officers.

Dependent:	**$Override_{LoanOfficer}$**			
	Coefficient (Std. Error)			
	(1)	**(2)**	**(3)**	**(4)**
Independent	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**
Control	0.127	0.0792	0.230	-0.420*
	[0.0829]	*[0.0619]*	*[0.379]*	*[0.245]*
Qualitative Score			1.389**	0.544**
			[0.684]	*[0.267]*
Qualitative Score * Control			-0.212	0.867**
			[0.722]	*[0.424]*
Size	0.334***	0.342***	0.193*	0.248**
	[0.118]	*[0.130]*	*[0.110]*	*[0.122]*
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Calculated Rating FE	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS
R-squared	0.191	0.171	0.221	0.196
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	1,701	1,659	1,701	1,659

Panel C: Corrections

Panel C presents linear estimation results for the Correction by the Approver as dependent variable. Columns (1) and (3) present estimation results for Low Experience loan officers, columns (2) and (4) present estimation results for High Experience loan officers

Dependent:	**$Correction_{Approver}$**			
	Coefficient (Std. Error)			
	(1)	**(2)**	**(3)**	**(4)**
Independent	**Low Experience**	**High Experience**	**Low Experience**	**High Experience**
Qualitative Score	0.0318	-0.0256		
	[0.184]	*[0.234]*		
$Override_{LoanOfficer}$			-0.213***	-0.138***
			[0.0412]	*[0.0307]*
Size	0.0460	-0.122	0.132	-0.0521
	[0.128]	*[0.0790]*	*[0.121]*	*[0.0827]*
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Calculated Rating FE	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS
R-squared	0.046	0.053	0.097	0.082
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	1,427	1,026	1,427	1,026

Our results show that experienced loan officers are more strongly affected by *Control* than their inexperienced peers. In Panel A, which examines the impact of *Control* on the *Proposed Rating* of a client, we find that experience roughly doubles the positivity-bias in loan officer discretion. For *Low Experience* loan officers, we find an insignificant point estimate for *Control* of 0.104. For *High Experience* loan officers, this value increases to statistically significant 0.205***. We find similar results for differences in the *Qualitative Score* (*Low Experience*: 0.0179; *High Experience*: 0.0601***), the *Industry Score* alone (*Low Experience*: 0.0172; *High Experience*: 0.0394**), and the *Individual Score* (*Low Experience*: 0.0190; *High Experience*: 0.0903***). Interestingly, experienced loan officers not only show a stronger positivity-bias under *Control*, but also distinctively focus on the less observable *Individual Score* of a client. Finally, when we look at the differences in the *Calculated Ratings*, we find that the differences in the qualitative assessment also result in different rating results. For experienced loan officers, we find *Calculated Ratings* that are, on average, 0.123** notches higher. As it seems, experienced loan officers do not only assign more positive qualitative assessments to customers, their bias also seems to more effectively target a better rating outcome. For inexperienced loan officers, on the contrary, we find consistently positive coefficients for all building blocks of the qualitative assessment, but in the end, the resulting *Calculated Rating* is, if anything, even lower under *Control* (-0.0162).[31]

Our results in Panel B show that experience not only affects the qualitative assessment, it also critically affects the *Override* behavior of a loan officer. All analyses in Panel B use the *Override* by loan officers as dependent variable. All remaining specifications are identical to our regression in Table 5-7. In columns (1) and (2), we present estimation results with *Control* as our independent variable of interest. In line with all previous results, we find that loan officers assign more positive *Overrides* under *Control*. This effect is more pronounced for inexperienced loan officers, but both point estimates are statistically insignificant (*Low Experience*: 0.127;

[31] In unreported additional analyses, we test the significance in differences between estimated coefficients of experienced and inexperienced loan officers using an interaction term on *Control* and *High Experience*. For the *Proposed Rating* as dependent variable, the coefficient (standard error) is 0.0982 (0.0971), for the *Qualitative Score* 0.0484** (0.0191), for the *Industry Score* 0.0326* (0.0196), for the *Individual Score* 0.0715*** (0.0269), and for the *Calculated Rating* 0.141** (0.0626).

High Experience: 0.0792).[32] In columns (3) and (4), we add a main effect of the *Qualitative Score* and an interaction term with *Control* to check if the loan officers' *Override* behavior is related to its previous qualitative assessment. The results not only show that there is in fact a relation between qualitative assessment and *Overrides*, they also provide an indication why the point estimates in column (1) and (2) are relatively low and not statistically significant. Experienced loan officers show a strong correlation between their qualitative assessment of a client and a subsequent *Override*. Depending on the qualitative assessment, an experienced loan officer assigns overrides that are roughly 0.4 rating steps more positive (negative) if the customer received the highest (lowest) possible *Qualitative Score* (*Qualitative Score* = 0: -0.420*; *Qualitative Score* = 1: 0.447**). This, however, is only true under *Control*. For inexperienced loan officers, on the contrary, *Control* does not have a significant impact. Inexperienced loan officers, however, show a generally higher sensitivity of *Overrides* to their qualitative assessment (1.389**).

In Panel C of Table 5-10, we show that, even though experienced loan officers drive most of our findings, approvers are in fact less likely to reverse the *Overrides* of experienced loan officers. Panel C uses the *Correction* by the approver as dependent variable and presents the results of our analyses on specification (1) and (5) of Table 5-8 using a sample split along loan officer experience. Our results in columns (1) and (2) indicate that approvers do not react differently to the qualitative assessment of experienced (0.0318) and inexperienced (-0.0256) loan officers. In columns (3) and (4), our estimation results show that loan officers are more likely to reverse an *Override* of an inexperienced loan officer (-0.213***) than of an experienced loan officer (-0.138***).[33] Overall, our results indicate that approvers hardly react to biased qualitative assessments, irrespective of the loan officers' experience. Approvers, however, seem to have distinctively less trust in *Overrides* by inexperienced loan officers as compared to *Overrides* by more experienced loan officers.

[32] Using an interaction term on *Control* * *High Experience* to test the differences between column (1) and column (2) yields a qualitatively similar, yet statistically insignificant coefficient (standard error) of -0.0524 (0.0680).

[33] Testing the differences in estimated coefficients between experienced and inexperienced loan officers confirms our interpretation. We find no differences in estimated coefficients as indicated by the insignificant point estimate of *Qualitative Score* * *High Experience* -0.262 (0.273) and a significant estimate for *Override* * *High Experience* 0.0754* (0.0432).

5.7. How Does Control Affect the Efficiency of the Rating Process?

5.7.1. Default as Measure for Efficiency

In this section, we want to relate our analyses to the effect of *Control* on the overall efficiency of the rating process. In their study, Hertzberg et al. (2010) provide evidence that the loan officers' assessment of a client is more efficient in predicting subsequent default if the likelihood of loan officer rotation, and hence the likelihood of being controlled by a newly assigned loan officer, is sufficiently high. We show that (i) if measured as in Hertzberg et al. (2010), preventive *Control* leads to less efficient credit ratings, (ii) this approach, however, might suffer from methodological flaws, and (iii) when measured from a resource-perspective, the benefit of using *Control* seems to be largely outweighed by its costs.

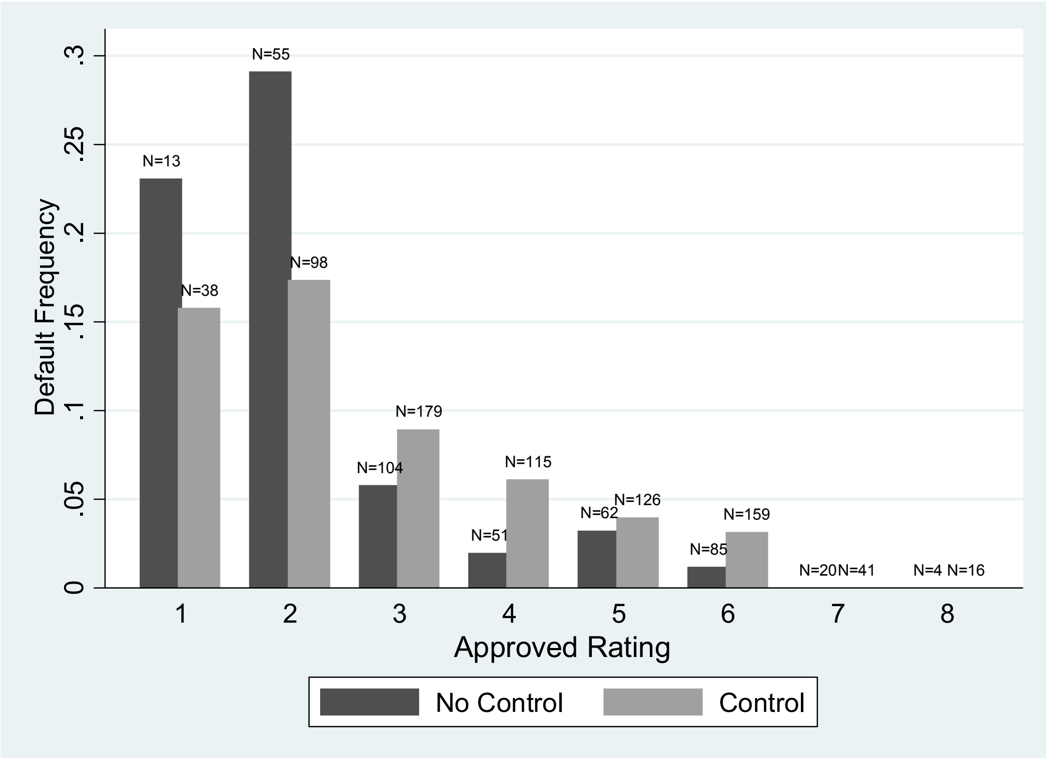
While Hertzberg et al. (2010) find that detective *Control* of loan officers leads to more efficient credit ratings by revealing otherwise withheld unfavorable information, we find that preventive *Control* induces loan officers to systematically assign better credit ratings to their clients. To test whether these differences in the concept of control also result in opposing effects on the efficiency credit rating process, we provide analogous analyses on the efficiency of ratings assigned by loan officers. We observe the legal default of a customer within two years after the rating application of a client.[34] We have complete default information on two banks in our total sample resulting in available observations for 1,166 clients and 85 defaults. In Figure 5-7, we present the distribution of the default frequencies across different *Approved Rating* classes dividing our sample into ratings that were controlled and those that were not. Both distributions show the typical distribution of default frequencies across rating classes with exponentially decreasing default incidences for higher rating classes. A more efficient rating model should assign lower ratings to clients that eventually default and higher ratings to those who survive. Figure 5-7 shows that, in our sample, controlled rating applications show a distinctively flatter slope than their uncontrolled peers. In particular, we find that default frequencies under *Control* are, compared to uncontrolled ratings, lower for the worst two rating classes and higher for rating

[34] Of course, realized default as a measure of the efficiency of a rating model requires the ex-ante true probability of default to consistently make the transition to default realizations. While this might not even necessarily be the case in general, it is even more unlikely during crisis periods or any systematic shifts in the relevant markets (Liberti and Mian, 2009).

classes three to six. For ratings of seven or eight, we do not observe any defaults in either subsample.

Figure 5-7: The Impact of Control on Default Prediction

This figure shows default frequencies across Approved Ratings. The observations are divided into controlled and uncontrolled applications. On top of each bar, the number of available observations is displayed.



The results on our multivariate regression, as adapted from Hertzberg et al. (2010), suggest that control leads to a less efficient rating model as indicated by the visual assessment. More thorough additional analyses, however, show that this effect is not statistically robust. All analyses in Table 5-11 employ Probit estimations and report marginal effects with *Default* as dependent variable.[35] We include the *Approved Rating* and an interaction term of the *Approved Rating* with *Control* as relevant independent variables. As in all previous analyses, we control for customer *Size* and include

[35] We do not present linear estimation results as a robustness test as estimated coefficients of both methodologies only converge if estimated default probabilities are clustered around 0.5. In this area, the Probit transformation would be sufficiently close to a linear transformation, justifying the use of a linear regression as approximation. In our case, however, with an average default frequency of roughly 7%, most of the observations are likely to have very low predicted default probabilities.

Industry and *Year* fixed effects in all regressions. Standard errors are, again, clustered on the loan officer level.[36]

Our baseline results in column (1) show that, while higher *Approved Ratings* lead to a strong reduction in the predicted probability of default (-0.0411***), this effect is significantly decreased (0.0176**) if a loan officer is controlled. Together with the main effect of *Control* (-0.0602), this translates into a steeper slope, and hence a supposedly more efficient rating model, for rating applications that are not controlled.[37] In column (2), we exclude any observations from our analyses that have a *Quantitative Score* higher than 0.75, as we observe very little defaults for these customers. Our estimation results remain qualitatively unchanged, but become distinctively more pronounced. When additionally looking at the subsamples for *Low Experience* and *High Experience* in columns (3) and (4), respectively, we find that, while losing most of the statistical significance, the loss in efficiency under *Control* is stronger for experienced loan officers.

The first important limitation to this approach is that it does not control for any differences in the sample composition of controlled and uncontrolled credit applications. Even though Table 5-4 presents evidence that mean values of *Default* are not statistically different for both subsamples, we further need to assume that *Defaults* are also similarly distributed across *Quantitative Scores*. If *Defaults* are differently distributed across rating classes, any effect we find in our regression might simply be picking up a-priori differences in the *Default* distribution.[38] To control for this issue, in columns (5) to (8) of Table 5-11, we add an additional main effect on the *Quantitative Score* and an interactions term of the *Quantitative Score* with *Control*. If there are systematic differences in the distribution of *Default* frequencies for controlled and uncontrolled observations, they should be picked up by these variables. Across all specifications, our results show that our previous finding is relatively robust to the

[36] Hertzberg et al. (2010) use a very similar approach: In their analyses, the risk rating is interacted with dummy variables on the “Quarter-to-Rotation”. These “Quarter-to-Rotation” variables indicate the likelihood of being controlled and are hence a probabilistic pendant to our *Control* variable.

[37] It is important to note, that overall *Default* frequencies in the Control and the No-Control subsamples are virtually identical. On average, both estimated regression lines should hence result in similar predicted default frequencies.

[38] This problem is more distinctively more pronounced in our setting as in the original Hertzberg et al. (2010) case, as their assignment of loan officer rotation is effectively random. However, with a similar absolute number of *Defaults* in their sample, the assumption of identical distributions across observable quality would need further verification.

additional control variables. While we lose any significance on the relevant estimation coefficients, their qualitative levels remain constant.

The second, more important, limitation to this approach is that its interpretation mainly depends on an interaction term of a non-linear regression. As pointed out by Ai and Norton (2003), an interaction term in a non-linear regression is distinctively different from an interaction term in linear regressions. Most importantly, the correct value and the statistical significance of the interaction term do not equal the coefficients reported in any standard statistical programs, but rather rely on each observation's predicted event probability (in this case *Default*). The approach presented in Table 5-11 as well as the one presented in Hertzberg et al. (2010), do not take this aspect into account. In Figure 5-8, we present the correct estimation results and its statistical significance for the interaction term on *Approved Rating* * *Control* in column (2) of Table 5-11. We use the module provided by Ai and Norton (2003) to estimate these values.

Figure 5-8, Panel A presents the correct values for the interaction effect in our second specification of Table 5-11 as well as the incorrect marginal effect. As the analysis uses data with very little events, i.e. *Defaults*, the relevant section with most observations is at low predicted probabilities. As Figure 5-8 points out, there are several observations whose correct interaction value is sufficiently close to the incorrectly estimated one. However, there is also a large share of observations that distinctively deviate from the incorrect line. Even more so, correct values deviate in both directions of the incorrect marginal effect, making a concluding interpretation of the actual impact of control on the efficiency of rating model using this approach hardly possible.

Table 5-11: Impact of Control on Proposed Rating

This table shows the results of a probit regression with the Default of a client as dependent variable. The values reported are marginal effects with standard errors, clustered on the loan officer-level in brackets. Columns (1) and (5) show the results for our full sample of observations with default information. Columns (2) and (6) include only observations with a Quantitative Score lower than 0.75. Columns (3) to (4) and (7) to (8) additionally split observations into loan officer with Low Experience and High Experience, respectively. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Table 5-1 for definitions on all variables.

Dependent:	**Default**							
	Marginal Effects (Std. Error)							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Independent	**All**	**Quant. Score < 0.75**	**Quant. Score < 0.75; Low Experience**	**Quant. Score < 0.75; High Experience**	**All**	**Quant. Score < 0.75**	**Quant. Score < 0.75; Low Experience**	**Quant. Score < 0.75; High Experience**
Control	-0.0602	-0.243*	-0.110	-0.321	-0.0550	-0.308	-0.244	-0.486
	[0.0404]	*[0.129]*	*[0.180]*	*[0.231]*	*[0.0742]*	*[0.238]*	*[0.429]*	*[0.305]*
Approved Rating	-0.0411***	-0.129***	-0.117*	-0.0974	-0.0304***	-0.106**	-0.0880	-0.0824
	[0.00796]	*[0.0360]*	*[0.0632]*	*[0.0790]*	*[0.00982]*	*[0.0426]*	*[0.0644]*	*[0.0526]*
Approved Rating * Control	0.0176**	0.0809*	0.0482	0.106	0.0153	0.0620	0.0325	0.0781
	[0.00836]	*[0.0429]*	*[0.0689]*	*[0.0955]*	*[0.0128]*	*[0.0521]*	*[0.0717]*	*[0.0721]*
Size	-0.0174	-0.0462	-0.140	0.0524	-0.0224	-0.0472	-0.164	0.0574
	[0.0280]	*[0.104]*	*[0.149]*	*[0.171]*	*[0.0284]*	*[0.102]*	*[0.152]*	*[0.167]*
Quant. Score					-0.113	-0.218	-0.442	-0.143
					[0.0962]	*[0.274]*	*[0.515]*	*[0.314]*
Quant. Score * Control					0.00555	0.158	0.238	0.320
					[0.104]	*[0.339]*	*[0.567]*	*[0.442]*
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
R-squared	0.166	0.115	0.106	0.202	0.172	0.117	0.110	0.208
Clustered Standard Errors	LO	LO	LO	LO	LO	LO	LO	LO
# Rating Applications	1,063	401	202	155	1,063	401	202	155

Even though our Probit estimate in column (2) of Table 5-11 reports a significant interaction term of the *Approved Rating* with *Control*, the correct estimation results for the z-statistic of the interaction term in Panel B of Figure 5-8 show a different picture: Z-statistics of most interaction terms are very close to zero and the respective interaction terms hence far from being statistically significant. Yet again, the wide distribution of z-statistics does not allow a meaningful interpretation of the interaction terms in general. To strengthen this view, in Table 5-12, we present summary statistics on the findings of Figure 5-8. The mean of the correct estimate for the interaction term is relatively close to the one reported in the respective estimation in Table 5-11 (mean Table 5-12: 0.104; Table 5-11: 0.0809*). The actual values, however, range from close to zero (0.00172) to more than triple the mean (0.350). Additionally, summaries on standard errors (mean: 0.0963) and the z-statistic (mean: 0.972) support the notion that the simple interpretation of the interaction term is not statistically robust.

Table 5-12: Correct Estimates for the Interaction Term on Control and Approved Ratings

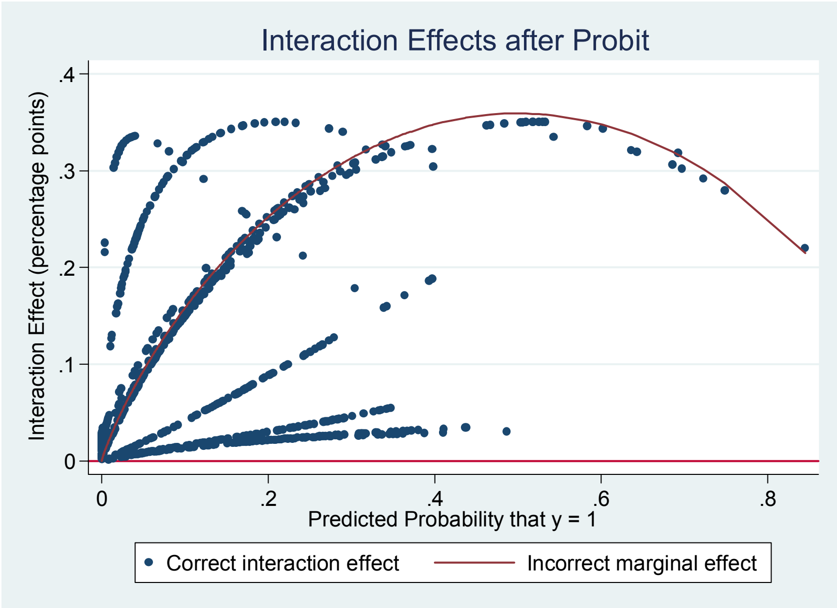
This table presents summary statistics on the correct estimates for the interaction term between Control and Approved Ratings as presented in Table 5-11, column (2).

Variable	Obs.	Mean	Std. Dev.	Min	Max
Interaction Term	840	0.104	0.109	0.00172	0.350
Standard Error	840	0.0963	0.0352	0.00972	0.215
Z-Statistic	840	0.972	0.896	0.133	4.244

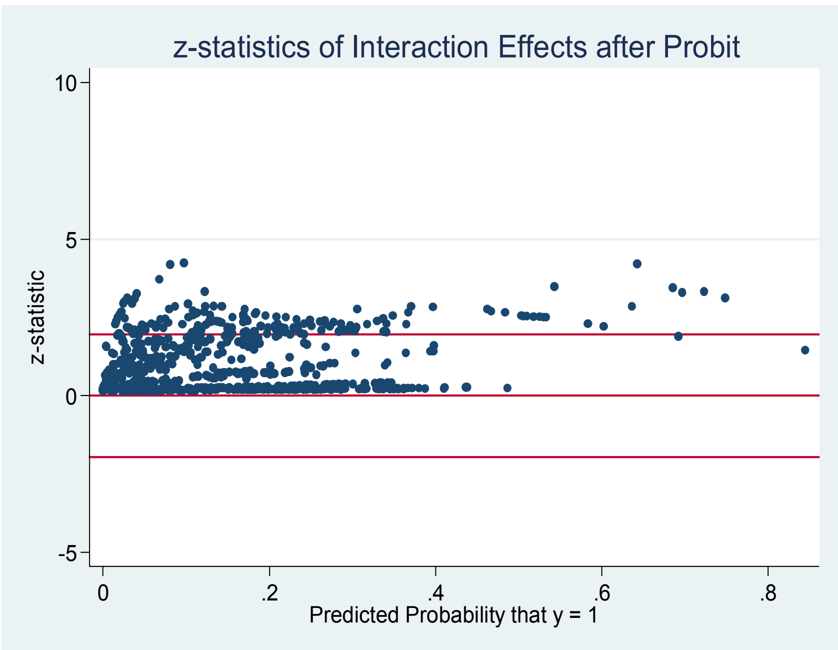
Figure 5-8: Interpretation of Interaction Terms in Default Prediction

These figures show the correct estimation results (Panel A) and z-statistics (Panel B) of the interaction terms of Control with Approved Ratings. We use the module provided by Ai and Norton (2003) to estimate these values.

Panel A: Interaction Effect after Probit



Panel B: Z-Statistics of Interaction Effects after Probit

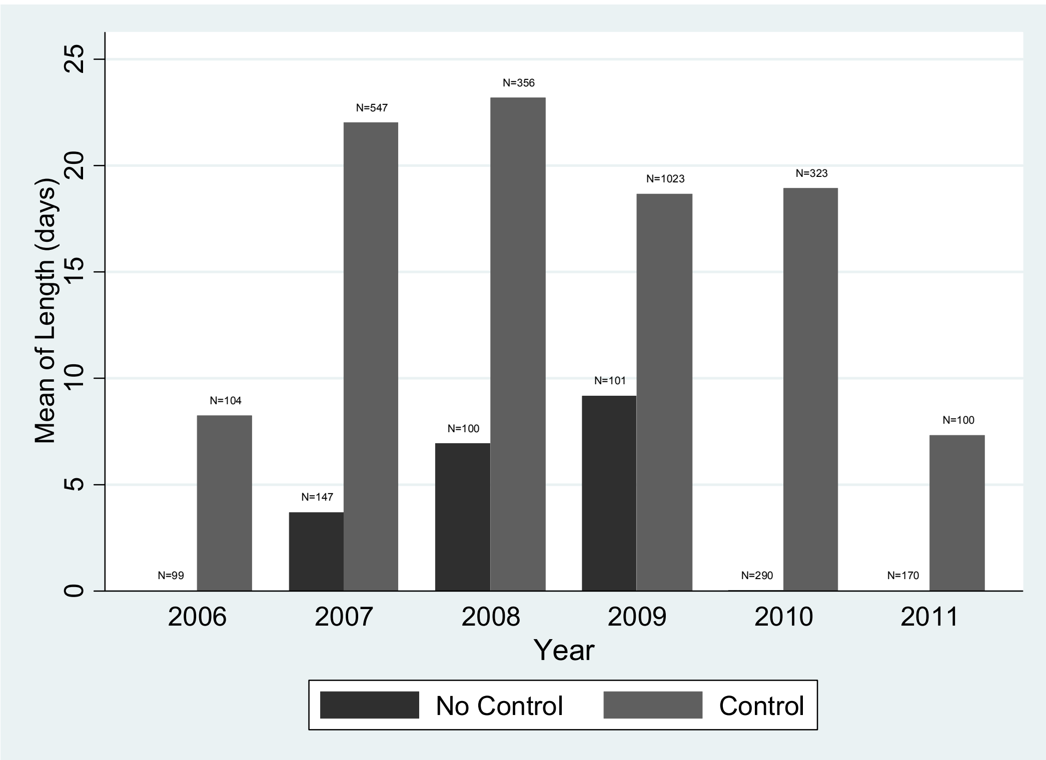


5.7.2. Applications Length as Measure for Efficiency

Rather than using an ex-post analysis on the realized *Default* frequency as a measure for the efficiency of the rating process, we propose a different approach that focuses on the efficiency of the process from a resource perspective. Thus far, our main results show that, under *Control*, loan officers assign more positive ratings to their customers. While it is hard to assess whether the controlled ratings are better able to predict *Default*, another important aspect is whether the differences in the rating assessment justify the additional cost incurred by controlling a loan officer. To answer this question, we first analyse how much longer it takes to approve a rating under *Control*. In Figure 5-9, we plot the mean number of days between the initial loan application of a customer and the final approval of the rating for different years in our observation window. In general, values differ quite substantially over time. However, controlled rating applications take consistently longer to approve than their uncontrolled peers. These differences range between seven and almost twenty days.

Figure 5-9: Development of Length of the Rating Process over Time

This figure presents the average (in days) for a rating application to be finally approved. Observations are divided by control and sorted by the year the applications is initiated in.



Similarly, the results in Table 5-13 show that, under *Control*, the rating application process takes on average roughly two weeks longer. In a standard linear regression, we use the days between the initial loan application and rating approval as dependent variable. Other control variables remain unchanged to the previous analyses. In column (1), we present the estimation results for our full sample. Under *Control*, the rating process takes 14.54*** days longer. In the second column, we exclude any observations with *Quantitative Scores* higher than 0.75 as the assessment of initially bad clients might be more complex and hence require systematically more time. The results remain qualitatively unchanged with a point estimate of 13.93*** days. Columns (3) and (4) report the finding when we apply a median-split to divide our full sample of column (2) by loan officer experience. While both estimations remain at high levels and statistically significant, we find that highly experienced loan officers actually take longer to complete a loan application (16.13***) than their inexperienced peers (10.62***). This result is surprising at first as one could expect experienced loan officers to have more routine and hence quicker in assessing a client's creditworthiness. In light of our previous findings, however, it rather seems that loan officers simply take (or need) more time to adjust the rating result as desired, which increases the length of the rating application.[39]

Our results show that loan officers assign customers significantly better ratings when they are controlled. We also find that approvers react to the (observable) bias in the loan officers' behavior and loan officers, in turn, learn from their experience with an approver. In the end, a controlled application process also takes significantly longer to approve. With these findings in mind: Is it worth the trouble? Our results suggest it is not.

[39] We confirm the statistical significance in differences for estimates on the two subsamples. Using an interaction term on *Control * High Experience*, we find that applications of experienced loan officers under control take 14.378 (8.706) days longer than under no control. Interestingly, the main effect of *High Experience*, in fact, yields a 10.280 days shorter application period.

Table 5-13: The Impact of Control on the Length of the Rating Process

This table presents linear estimation results for the length of the rating process in days. Standard errors are clustered on the loan-officer level. Column (1) shows the results for our full sample of available observations. Column (2) includes only observations with a Quantitative Score lower than 0.75. Columns (3) to (4) additionally split observations into loan officers with Low Experience and High Experience, respectively. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. See Table 5-1 for definitions on all variables.

Dependent:	**Length of Rating Process (d)**			
	Coefficient (Std. Error)			
	(1)	**(2)**	**(3)**	**(4)**
Independent	**All**	**Quant. Score < 0.75**	**Quant. Score < 0.75; Low Experience**	**Quant. Score < 0.75; High Experience**
Control	14.54***	13.93***	10.62***	16.13***
	[2.012]	*[3.603]*	*[3.753]*	*[2.650]*
Size	4.582	-0.140	2.134	8.303
	[4.560]	*[6.660]*	*[6.471]*	*[6.897]*
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Calculated Rating FE	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS
R-squared	0.028	0.046	0.028	0.052
Clustered Standard Errors	LO	LO	LO	LO
# Rating Applications	3,360	1,248	1,700	1,660

When looking on the impact of *Control* on the entire rating application process, including potential *Corrections* by approvers, we find that rating results are not significantly different under *Control*. In Table 5-14, we repeat our main regression from Table 5-5. Instead of using the *Proposed Rating* as dependent variable, this time, however, we use the *Approved Rating*. We thus extend our analysis not only to the influence of *Control* on the loan officer but also incorporate the approvers' *Corrections* in our analysis. Across all specifications, we find a statistically insignificant impact of *Control* on the *Approved Rating*. As expected though, the point estimates still consistently arrive at positive values. For the specification in column (1), for example, the magnitude of the *Control*-coefficient shrinks to roughly a third of its value without the approvers' corrections (0.0621). For the subsample with lowest *Quantitative Scores*, the impact of *Control* is 0.0439. For the clients in the mid-section, the impact is essentially zero with a point estimate of 0.00180. Only for clients with high *Quantitative Scores*, the impact of *Control* prevails at an economically relevant, yet statistically insignificant value of 0.140. These findings are in line with our previous observations which demonstrate that (i) approvers are relatively insensitive to manipulations through the qualitative assessment of a client and (ii) clients with high *Quantitative Scores* benefit, to a large part, from higher *Qualitative Scores* rather than *Overrides*.[40]

Table 5-14: The Impact of Control on the Approved Rating

This table presents linear estimation results for the impact of Control on Propsed Ratings. Standard errors are clustered on the loan officer level. Statistical significance of estimation results at the 10% / 5% / 1%-level are indicated by * / ** / *** after the coefficient. Column (1) presents our baseline regression including all available observations. Columns (2) to (4) show the results for three subsamples depending on the impact of the Qualitative Score on the Calculated Rating. See Table 5-1 for detailed definitions on all variables

Dependent:	**Approved Rating**			
	Coefficient (Std. Error)			
	(1)	**(2)**	**(3)**	**(4)**
Independent	**All**	**No Influence**	**Increasing Influence**	**High Influence**
Control	0.0621	0.0439	0.00180	0.140
	[0.0614]	*[0.0634]*	*[0.0927]*	*[0.0904]*
Quant. Score	9.915***	4.349***	17.77***	7.569***
	[0.211]	*[0.292]*	*[0.889]*	*[1.170]*
Size	0.781***	0.277***	0.217	1.829***
	[0.116]	*[0.105]*	*[0.177]*	*[0.260]*
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Method	OLS	OLS	OLS	OLS
R-squared	0.686	0.253	0.344	0.155
Clustered Standard Errors	Loan Officer	Loan Officer	Loan Officer	Loan Officer
# Rating Applications	3,360	1,248	983	1,129

5.8. Conclusions

In this paper, we examine how preventive *Control* affects the loan officers' behavior in the credit assessment of small corporations. We find that ratings proposed by loan officers are, on a rating scale from one to eight, roughly 0.2 steps higher if they are controlled by a second person.

[40] Insignificance in differences between *No Influence* and *Increasing Influence* as well as significance in differences between *No Influence* and *High Influence* are confirmed by additional analyses that employ respective interaction terms. Using an interaction term on *Increasing Influence * Control* yields an estimation result of -0.0669 (0.122), the interaction term on *High Influence * Control* results in an estimation of 0.231* (0.108).

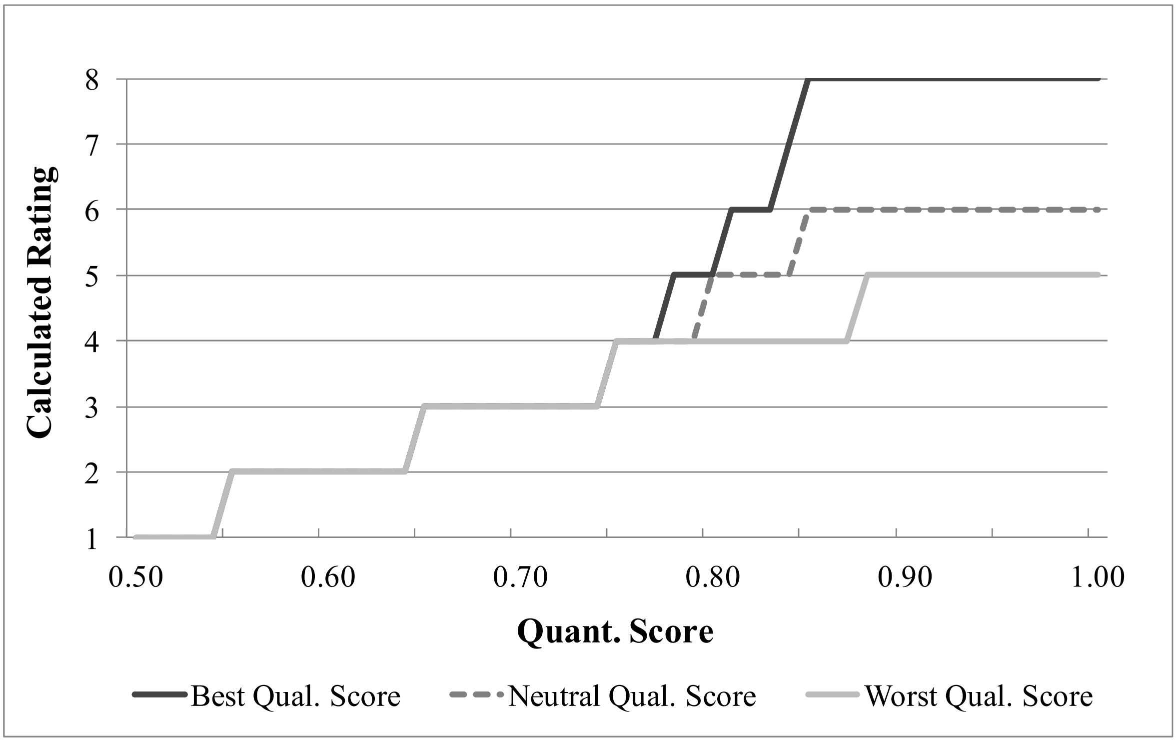
We find that these differences are not compatible with the view that loan officers assign more efficient ratings under *Control*: If anything, ratings proposed by loan officers under control are even less efficient in predicting future default. Additionally, loan applications consume significantly more of the bank employees' resources while, after final corrections by approvers, yielding results that are statistically indistinguishable from uncontrolled ratings. In contrast, our results are compatible with hidden costs of control: In anticipation of potential downgrades by the approver, loan officers adjust their assessments over time, assigning more positive *Qualitative Scores* and *Overrides*. In line with this view, we find that differences in rating assessments are more pronounced for experienced loan officers and for loan officers that were frequently downgraded in previous assessments. Additionally, experienced loan officers appear to skillfully hide their activities from the approvers by manipulating less observable input parameters of a rating. Overall, it seems as if experience rather allows loan officer to more efficiently trick the rating process rather than to more efficiently acquire valuable information about the clients.

Our results have important practical implications for bankers and regulators: Our results raise doubt about the widespread use of the four-eye principle in rating application processes. It seems that loan officers use a large part of their discretion in the credit rating process to anticipate the approvers' corrections rather than to actually improve the rating. As a consequence, banks incur additional personnel cost to control loan officers, without creating any significant additional value. In light of the increasing importance of internal credit rating processes under Basel II (and Basel III), banks and regulators should have a strong incentive to insure an efficient use of the resources that contribute to the credit rating process.

Additionally, our results shed light on the importance of the different concepts of control in the banking environment. Recent empirical evidence suggests that (detective) *Control* triggers more efficient use of information in credit assessments. As our results point out, when focusing on the, in banking context, more relevant concept of preventive *Control*, results actually appear to be the other way around with *Control* leading to less efficient rating processes.

Appendix 5-I: Calculated Rating as a Function of Quantitative Score and Qualitative Score

Appendix I presents the conversion mechanics from the Quantitative Scores to the Calculated Rating. The different lines represent the rating results for a hypothetical rating with a best, worst and neutral qualitative assessment. Quantitative scores below 0.5 result in a Calculated Rating of one, irrespective of the Qualitative Score. For a detailed definition of the variables, see Table 5-1.



Appendix 5-II: Exemplary Rating Application Form

Appendix 5-II presents a stylized design for the graphical user interface of the rating tool for SMEs used at the banks in our data sample. The first section includes basic information on the customer and the date of the application. This section also reports the calculated rating score and the resulting Calculated Rating. The second section requires the loan officer to input the relevant quantitative information on the customer. For each of the seven different ratios, the quantile the current customer is in, is displayed. Besides the ratios, the rating model also includes additional quantitative information on two items that need to be answered categorically. The following section processes the qualitative information on the customer. Each question is designed to choose between three to four categorical assessments. In the final section, the loan officer may calculate the rating and potentially redo his / her assessment before proceeding and saving the results.

Credit Rating Application for SMEs

Customer:	XXX
Date of Financial Statement:	MM/DD/YYYY
Date of Rating:	MM/DD/YYYY
Calculated Rating	
Calculated Score	

Input for Quant. Score

		Quantile 1	2	3	4	5
Ratio 1	x%		■			
Ratio 2	x%				■	
Ratio 3	x%					■
Ratio 4	x%		■			
Ratio 5	x%		■			
Ratio 6	x%	■				
Ratio 7	x%					■

Additional Information 1	category 1 / category 2 / category 3
Additional Information 2	category 1 / category 2 / category 3

Input for Qual. Score

Qual. Score 1	good / average / weak
Qual. Score 2	good / above average / average / below average / weak
Qual. Score 3	very good / good / average / weak
Qual. Score 4	good / average / weak
Qual. Score 5	good / average / weak
Qual. Score 6	good / average / below average / weak / very weak
Qual. Score 7	very good / good / average / weak

Calculate Rating

Save & Proceed

References

Ai, C. and Norton, E. (2003): “Interaction Terms in Logit and Probit Models”, *Economic Letters*, 80, 123 – 129.

Basle Committee on Banking Supervision (1998): “Framework for Internal Control Systems in Banking Organizations”, Basle, 1998.

Berger, A., Miller, N., Petersen, M., Rajan, R., and Stein, J. (2005): „Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks”, *Journal of Financial Economics*, 76, 237 – 269.

Cerquiero, G., Degryse, H., and Ongena, S. (2011): “Rules versus Discretion in Loan Rate Setting”, *Journal of Financial Intermediation*, 20 (4), 503 – 529.

Christ, M., Sedatole, K., Towry, K., and Thomas, M. (2008): “When Formal Controls Undermine Trust and Cooperation”, *Strategic Finance*, January, 38 - 44.

Christ, M., Emett, S., Summers, S., and Wood, D. (2012): “The Effects of Preventive and Detective Controls on Employee Performance and Motivation”, *Contemporary Accounting Research*, 29 (2), 432 – 452.

Degryse, H., Liberti, J., Mosk, T., and Ongena, S. (2012): “Is Loan Officer Discretion Advised When Viewing Soft Information?”, Working Paper, 2012.

Grunert, J., Norden, L., Weber, M. (2005): “The Role of Non-Financial Factors in Internal Credit Ratings”, *Journal of Banking & Finance*, 29, 509 – 531.

Hertzberg, A., Liberti, J., and Paravasini, D. (2010): “Information and Incentives inside the Firm: Evidence form Loan Officer Rotation”, *Journal of Finance*, LXV (3), 795 – 828.

Ledgerwood, J. and White, V. (2006): “Transforming Microfinance Institutions: Providing Full Financial Services to the Poor”, World Bank Publications, Washington.

Liberti, J. and Mian, A. (2009): “Estimating the Effect of Hierarchies on Information Use”, *Review of Financial Studies*, 22 (10), 4057 – 4090.

Qian, J., Strahan, P., and Yang, Z. (2011): "The Impact of Incentives and Communication Costs on Information Production: Evidence from Bank Lending"; Working Paper, 2011.

Romney, M. and Steinbart, P. (2009): "Accounting Information Systems", Prentice Hall, 11th Edition, Upper Saddle River, NJ.

Scott, J. (2006): "Loan Officer Turnover and Credit Availability for Small Firms", *Journal of Small Business Management*, 44 (4), 544 – 562.

Stein, J. (2002): "Information Production and Capital Allocation: Decentralized versus Hierarchical Firms", *Journal of Finance*, LVII (5), 1891 – 1922.

Uchida, H., Udell, G., and Yamori, N. (2012): "Loan Officers and Relationship Lending to SMEs", *Journal of Financial Intermediation*, 21 (1), 97 – 122.

6. The Liquidity Dynamics of Bank Defaults

Stefan Morkoetter*, Matthias Schaller**, Simone Westerfeld***

Forthcoming: European Financial Management

Abstract

We compare liquidity patterns of 10,979 failed and non-failed US banks from 2001 to mid-2010 and detect diverging capital structures: Failing banks distinctively change their liquidity position about three to five years prior to default by increasing liquid assets and decreasing liquid liabilities. The build-up of liquid assets is primarily driven by short term loans, whereas long term loan positions are significantly reduced. By abandoning (positive) term transformation throughout the intermediate period prior to a default, failing banks drift away from the traditional banking business model. We show that this liquidity shift is induced by window dressing activities towards bondholders and money market investors as well as a bad client base.

Keywords: Liquidity, bank default, capital structure, income structure

JEL Classification: G21

---

* University of St. Gallen (e-mail: stefan.morkoetter@unisg.ch), ** University of St. Gallen (e-mail: matthias.schaller@unisg.ch), *** University of Applied Sciences Northwestern Switzerland (e-mail: simone.westerfeld@fhnw.ch)

We would like to thank an anonymous referee and John Doukas for their helpful comments. We also thank Martin Brown, Matthias Hoffmann, and the participants of the CEQURA 2010 Conference in Munich, the SGF 2011 Conference in Zurich, the Annual Meeting of the German Academic Association for Business Research in Kaiserslautern and the SUERF 2011 Conference in Brussels for their comments and useful discussions on the ideas contained in this paper.

6.1. Introduction

The latest financial crisis has pronounced the importance of liquidity issues especially for banks relying on capital market sources of funding. In particular, banks approaching a default situation put a strong emphasis on documenting their liquidity positions in order to avoid a bank run led by funding counterparties. Thereby, bank stability experienced a renaissance in importance and repositioned itself as the central concern of market participants, regulators and politicians. In order to re-establish creditability within the financial community banks were forced to build massive liquidity cushions.

Following this consideration, the basic research question of this paper is to analyse the developments of the capital structure for banks with regard to liquidity on their path towards default in comparison to their surviving peers. We aim at detecting different patterns between defaulting and non-defaulting banks: Do defaulted banks manage their liquidity positions differently than their surviving peers? What are the reasons underlying different liquidity structures? How does liquidity affect bank defaults? We are not only interested in the very recent months prior to a bank default but also in the medium to long-term aspect of liquidity management. For the purpose of our paper, we restrict the definition of bank liquidity to assets and liabilities with either highly efficient transaction markets or a maturity of three months at most.

Our basic finding with regard to capital structure is that failed banks distinctively change their liquidity position about three to five years prior to default by increasing liquid assets and decreasing liquid liabilities. This strengthening of the liquidity positions is then followed by a strong decrease in liquid assets which reverts the aforementioned change in the capital structure. Furthermore, we analyse potential reasons for banks to behave as differently as described and conclude that it is the banks governance structure and its impact induced by money market refinancing that drives the tendency towards a highly liquid balance sheet structure in ultimately defaulted banks. Additionally, we find that failing banks appear to have a distinctively worse client base: During times of economic distress, these banks face a strong increase in unused loan commitments that are drawn by struggling customers.

Based on these findings our paper contributes to the existing literature by three aspects: First, based on our analysis of the medium to long-term perspective we reveal – to our knowledge - new structural liquidity differences between failing and non-failing banks and explain these patterns with window dressing and a bad client base. Second, we are able to measure bank stability more directly via default than previous studies that mostly focus on market proxies of bank risk. Third, in contrast to existing research we observe that not income diversification drives the insolvency risk of banks, but (endogenous) changes in the liquidity relevant capital structure.

Current discussions on regulation and capital adequacy in the context of Basle III might benefit from our analysis as liquidity issues are considered to be one main shortfall of the Basle II documents besides pro-cyclicality of capital requirements. We complement this discussion by showing that balance sheet based liquidity is a helpful indicator of bank default in the medium- to long run.

The remainder of this paper is organized as follows: Section 2 presents the different branches of literature that are relevant to this topic. Section 3 introduces the data sample and the methodology that is used throughout the empirical parts of the paper. Section 4 presents our results, which are discussed in Section 5. Section 6 concludes the paper.

6.2. Literature Review

A large body of literature exists that deals with the topic of liquidity within banks and its impact on various factors (e.g. default risk). Financial literature considers capital structure as being at the heart of banks' defaults and bank runs. Within this approach, the bank's default risk is assessed by estimating the risk from the bank's assets, relating it to the bank's asset-to-liability ratio and considering incentives for future capital structure adjustments. Two strands of literature are relevant in this context: The first considers banks in a time-continuous setting where banks are subject to regulation, i.e. regulation requires the capital-to-asset ratio of banks to exceed a given level, and the deposit structure of banks is given exogenously, e.g. Fries et al. 1997. The second strand of literature concentrates on endogenous capital structure choices, e.g. Leland 1998. The firms considered in this strand of literature are not subject to regulation but default endogenously. Diamond and Rajan (2000) contribute to the question of bank capital structure and regulation by showing that optimal capital structure trades off effects on liquidity creation, cost of bank distress, and the ability to force borrower repayment. Using this literature as our starting point, we focus our analysis on liquidity aspects in the capital structure of banks while basing our discussion on individual bank-level data and not on a systemic view. Based on a theoretical framework, Bank and Lawrenz (2010) argue that banks with riskier assets rely to a lesser extent on deposit financing.

The second trait of relevant literature reaches beyond optimal capital structure and liquidity but focuses on profitability in the banking industry and its connection with default risk. In particular, income structure and diversification, competition, efficiency, and deposit insurance are analyzed (e.g. Goddard et al. 2010). In an empirical analysis of European banks, Lepetit et al. (2008) investigate the relationship between bank risk and income structure. The study shows that banks expanding into non-interest income activities present higher insolvency risk than banks which mainly supply loans. Demirgüç-Kunt and Huizinga (2010) support this finding of increased bank fragility associated with a high proportion of non-interest income and non-deposit funding. Altunsbas et al. (2007) document in a study on the relationship between efficiency and risk for the European banking sector a positive relationship between risk and the level of equity and liquidity and that inefficient banks tend to hold more capital but act less risky.

Profitability is also analyzed in the context of explanatory factors of bank failures. In his analysis of Latin America and East Asia during the nineties, Arena (2008) concludes that bank-level fundamentals significantly affect the likelihood of bank failure. Liquidity was tested within this study as a contributing factor. However, this analysis only reveals whether there were statistical differences in bank-level fundamentals between failing and non-failing banks. It does not isolate the contribution of particular variables (e.g. short-term deposit positions) to the probabilities or timing of failure.

In their article on bank risk taking and competition, Boyd and De Nicolo (2005) analyse risk-incentive mechanisms in banks that are triggered by increased competition. Allan and Gale (2004) go even further and argue that the relationship between competition and financial stability in the banking sector is considerably more complex than a simple trade-off. They argue based on the agency problem between bank owners and public deposit insurance: The bank managers have an increased incentive to take extra risk because of deposit insurance. This extra risk that banks take as a result of the agency problem might cause bank failures.

6.3. Data Sample & Methodology

6.3.1. Data Sample

Our empirical analysis is based on quarterly balance sheet as well as income statement data of all US banks and thrift institutions registered with and reported to the Federal Deposit Insurance Corporation (FDIC) for the time period 01/01/2001 – 6/30/2010. For financial years before 2001 the FDIC does not report quarterly figures. Therefore, our data sample is limited to a total of 9.5 consecutive years for which quarterly reports are available. Over the investigated time period, a total of 10,979 different financial institutions, with 8,746 on average, reported to the FDIC on a quarterly basis (see Table 6-1). 329 of these institutions either failed in the course of the sample period or needed an assistance transaction to be able to continue business. In the following, we refer to the subsample as failed banks (F). Since we are especially interested in the dynamics before a bank default, we exclude any defaults before 2006. As our data starts only in 2001, most of these defaults only include a small number of observations and hence simply introduce additional noise to our analysis. The exclusion only accounts for 21 cases, but leaves us with data on 308 failing banks with at least 20 observations (5 years) each. As a robustness check, we perform all analyses with the full set of defaults. The results, however, remain qualitatively unchanged. The second subsample amounts to 10,671 non-failed banks (NF), which reported at least once in the course of the observation period to the FDIC and neither defaulted nor required any assistance transactions.

For each year we display the number of reports available for the respective subsample (e.g. in 2001 there were 243 reports available of banks that eventually defaulted in the subsequent years). In order to avoid a selection bias we also include all quarterly reports submitted by banks that were acquired by a competitor in the course of the observation period. Comparability and correctness of the data points reported by the banks is ensured by the standardized FDIC sourcing process. This holds in particular for the classification of individual positions. We do not incorporate SEC-regulated investment banks, because i) they apply a different business model, ii) they do not report to the FDIC and therefore do not enjoy its deposit insurance scheme and iii) their clients have different incentive structures in terms of moral hazard perspectives. By limiting the data sample to FDIC-registered banks we ensure that all banks are obliged to a comparable regulation framework.

Table 6-1: Descriptive Statistics

This table presents the data from the Federal Deposit Insurance Corporation and contains quarterly balance sheet information of a total of 10,979 financial institutions for the years 2001 to 06/2010. The table reflects values as of the last available quarter of each year. The table lists the available number of reports for banks that failed (F) in the course of our observation period and banks that did not fail (NF) separately. The table also reports the number of bank defaults during the period 2006 to 2010. Additionally, the median and mean values of the number of employees and balance sheet total are listed.

Year	Reports Available NF	*Reports Available F*	*Bank Defaults*	Employees (Median) NF	*Employees (Median) F*	Employees (Mean) NF	*Employees (Mean) F*	Balance Sheet Total* (Median) NF	*Balance Sheet Total* (Median) F*	Balance Sheet Total* (Mean) NF	*Balance Sheet Total* (Mean) F*
2001	9,370	*243*	-	32	*41*	203	*282*	92,539	*121,341*	802,059	*1,474,895*
2002	9,104	*251*	-	34	*45*	213	*336*	99,201	*144,286*	881,085	*1,670,303*
2003	8,921	*261*	-	34	*48*	219	*362*	105,293	*165,808*	968,338	*1,690,209*
2004	8,704	*273*	-	34	*53*	231	*330*	110,805	*201,755*	1,101,966	*1,902,642*
2005	8,552	*283*	-	35	*59*	240	*380*	117,436	*233,198*	1,199,816	*2,209,967*
2006	8,391	*292*	*1*	36	*64*	251	*366*	123,235	*276,329*	1,334,150	*2,336,600*
2007	8,247	*292*	*4*	36	*67*	256	*373*	129,160	*291,574*	1,500,202	*2,320,210*
2008	8,048	*261*	*57*	37	*61*	263	*164*	138,388	*292,407*	1,691,035	*1,053,367*
2009	7,893	*127*	*160*	37	*50*	260	*115*	149,629	*262,771*	1,652,827	*631,744*
H1 - 2010	7,857	*86*	*86*	37	*47*	257	*136*	152,344	*274,495*	1,695,663	*720,887*
Total	**10,671**	***308***	***308***	**35**	***53***	**238**	***307***	**119,217**	***217,613***	**1,264,266**	***1,740,283***

** in thousand USD*

In the first year, the sample of non-failing institutions contains 9,370 reports. This number continuously decreases to 7,857 reports filed at the end of 06/2010. The decrease of filed reports is simply a result of industry consolidation through mergers and acquisitions. The pattern behind the number of reports available for failed institutions is impacted by the recent financial crisis. Throughout the period before the current crisis, the number of reports filed every year slightly increased from 243 in 2001 to 292 in the period just before the financial crisis started in 2007. With an increasing number of banks defaulting from the beginning of 2007, this figure starts to decrease until the end of mid-2010 (86). In the last two years, the failed sample decreases dramatically as the majority of the failures happened within these two years. Generally, the failed sample contains larger institutions in terms of workforce and balance sheet total than the sample of non-failing institutions. The median of failing banks employs 53 full time equivalents (FTE) whereas the median of non-failing banks employs only 35 FTEs. The respective mean values are by far larger, which is due to the largest banks in both samples that skew mean values to higher levels. Similar relations are also reflected in the balance sheet total as a second proxy for bank size. The average failed bank tends to be bigger in terms of pure size attributes.

Table 6-2 relates to the average capital structure of both failed and non-failed banks. The figures are based on average mean values calculated on the basis of all available quarterly results. Following the traditional business model of banks, the asset side is dominated for both subsamples (failed and non-failed) by the position "securities" and "net loans & leases", whereas "securities" in turn is dominated by debt instruments (approx. 97%). However, with the subsample of failed banks being less exposed towards "securities" than observed in the case of non-failed banks, we already detect first signs of different asset structures. In terms of financing sources, failed banks have on average a lower equity base (10.02%) than observed in the case of non-failed ones (11.76%).

6.3.2. Methodology

In order to define a liquidity-driven capital structure, we first identify liquidity-relevant asset (LRA) and liability (LRL) positions. We base our definition of bank liquidity on a two-step approach: First, we include all assets which can be sold on highly efficient and liquid markets and all liabilities which can be withdrawn from depositors and creditors on short-notice (e.g. daily). Second, if this criterion is not applicable, all assets and liabilities with a maturity of less than three months are viewed as short-term and are therefore relevant for our analysis. In times of turbulences, short maturity structures on the asset side should allow banks to service capital outflows towards depositors and investors of short-term liabilities. The inclusion of each liquidity position is based on the consideration of how quickly an asset can be turned into cash at a predictable price or how quickly the funding is withdrawn from a bank in times of stress scenarios. Assets and liabilities with long maturities in turn are not suitable to offer comparable access to liquidity. One may argue that other balance sheet positions with maturity structures exceeding three months, e.g. long-term loans, can also be sold to third parties through securitization transactions. However, we do not follow this argumentation since it requires a rather long structuring time or might not be accessible at all for originators (e.g. recent financial crisis).

Based on these considerations we group the selected balance sheet positions according to liquid assets and liquid liabilities. Table 6-3 provides a detailed overview of the selected asset and liability positions. Since the liquid security positions are quite insignificant in size, we refrain from adding a discount for potential market illiquidity. We assume that for a bank approaching a default situation, the funding counterparts (both national and international depositors as well as institutional investors and trading counterparts) will withdraw their capital according to their legal ability to do so. Thus, in times of stress, banks with a higher degree of short term debt are more exposed to cash withdrawals and therefore incorporate a higher risk of a bank run. Banks with a high portion of liquid assets in turn experience fewer difficulties to serve these capital outflows by selling-off liquid assets. Additionally, we note that the larger the gap between short-term assets and short-term liabilities, the larger the term transformation.

Table 6-2: Average Balance Sheet Structure of the Non-Failed and the Failed Sample

This table presents the average composition of the balance sheet of banks that failed in the course of our sample period and banks that did not fail. Our data contains quarterly reports to the FDIC for the period 2001 to H1-2010. The percentage values constitute the means of the pooled values of both groups. The most relevant positions are subdivided into several additional levels, each additional level marked by indention. The percentage values in each subdivision are stated in terms of the total balance sheet size.

Assets	Non-Failed	Failed	Failed	Non-Failed	Liabilities
Cash and due from depository institutions	**5.58%**	**4.44%**	**80.33%**	**80.86%**	***Total deposits***
Securities	**22.19%**	**13.66%**	3.94%	11.69%	*Foreign Deposits*
Equity Securities	0.56%	0.39%	76.39%	69.17%	*Domestic Deposits*
Debt Securities	21.63%	13.27%	13.60%	17.22%	*Transaction Accounts*
Mortgage pass-through securities backed by	4.42%	3.20%	62.79%	51.96%	*Non-Transaction Accounts*
closed-end first lien 1-4 family residential mortgages			12.86%	10.28%	*Money-market Deposit Accounts*
Other mortgage-backed securities	1.76%	1.75%	6.96%	8.34%	*Other Savings Deposits*
Fixed and floating rate debt securities	15.45%	8.32%	42.96%	33.34%	*Time Deposits*
Federal funds sold & reverse repurchase agreements	**4.07%**	**4.35%**	**2.02%**	**1.51%**	***Federal funds purchased & repurchase agreements***
Net loans & leases	**62.95%**	**71.78%**	**6.76%**	**4.85%**	***Other borrowed funds***
Loss Loan Allowance	-1.48%	-1.68%			
Unearned Income	-0.09%	-0.11%			
Loans & leases	64.52%	73.57%			
Fixed and floating rate closed-end loans secured	15.39%	10.87%			
by first lien on 1-4 family residential properties					
All Other Loans and Leases	49.13%	62.70%			
Trading account assets	**0.05%**	**0.03%**	**0.00%**	**0.01%**	***Trading liabilities***
Bank premises and fixed assets	**1.83%**	**1.93%**	**0.07%**	**0.04%**	***Subordinated debt***
Other real estate owned	**0.23%**	**0.64%**	**0.80%**	**0.97%**	***All other liabilities***
Goodwill and other intangibles	**0.53%**	**0.55%**	**10.02%**	**11.76%**	***Total equity capital***
All other assets	**2.57%**	**2.62%**			
Total	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**Total**

We provide a first overview on liquidity-relevant positions for both failed and non-failed banks covering the whole time period in Table 6-4. For each year we calculate the corresponding mean and median figures based on balance sheet statements available for a given year. In terms of assets we observe that failed banks tend to invest their capital into liquidity-relevant assets to a higher degree than non-failed banks. On the liability side in turn, non-failed banks are exposed, on average, to a higher degree of liquidity-relevant financing as compared to failed banks. Thus, we find first signs that positive maturity transformation is more pronounced in the case of non-failed banks. As already outlined in Table 6-2, equity ratios are lower for failed banks.

For the following empirical analysis we structure the data from the sample of 10,979 different quarterly balance sheets according to a time-to-default perspective (see Appendix 6-I). This time-to-default perspective allows us to investigate diverging patterns in terms of balance sheet structure between failed and non-failed banks. Starting with the subsample of failed banks, we first determine the quarter in which a bank defaulted or received an assistance transaction by the FDIC. Based on this quarter we assemble the individual quarters prior to the default quarter for each failed bank. In a second step we calculate for each of these quarters the corresponding mean and median values for all banks that do not default between 2001 and the first half of 2010 and that filed a quarterly statement with the FDIC. For each defaulting bank, the respective non-failed sample is built using the actual, real-time values of the non-failed sample. Accordingly, the figures for the non-failed sample are weighted based on the default pattern of the failed banks. Appendix 6-I displays the aggregated results for failed and non-failed banks from a rather default-driven perspective. Here, and in all further analyses, $t = 0$ represents the default point of each bank with $t = -1$ and so on referring to an ex-ante default perspective (e.g. $t = -1$ equals the last quarterly results prior to the default quarter). This approach ensures that any changes in industry dynamics during the observation period are accounted for. The empirical section that follows is based on this default-driven matching algorithm. We restrict our analysis to the period 5 years prior to default. Since we have at least 5 years of observation for every failed bank, we can ensure that our analysis is consistent in this period and might not be driven by left-censoring effects.

Table 6-3: Liquidity Relevant Asset and Liability Positions

This table presents the liquidity-relevant balance sheet positions according to our understanding of bank liquidity. The definitions of the positions, as the data itself, are retrieved from the Federal Deposit Insurance Corporation. Liquidity-relevant is based either on the existence of liquid transaction markets or a maturity of three months or less.

Short-Term Assets

Cash & Cash-comparable:

- Cash & Balances due from depository institutions (CHB).
- Federal funds sold and reverse repurchase: Total federal funds sold and securities purchased under agreements to resell in domestic offices (FRE).
- Trading Accounts: Securities and other assets acquired with the intent to resell in order to profit from short-term price movements (TRA).

Securities:

- Mortgage pass-through securities backed by closed-end first lien 1-4 family residential mortgages with a remaining maturity of three months or less (SCM).
- Fixed and floating rate debt securities including securities that are issued by the US Treasury, US government agencies, and states and political subdivisions. (SCF).
- Total equity securities available-for-sale at fair value not held in trading (SCE).

Loans (net, with a maturity of <3 months):

- Fixed and floating rate closed-end loans secured by first lien on 1-4 family residential properties held in domestic offices with a remaining maturity of three months or less (LOF).
- All other loans and leases (other than closed-end loans secured by first lien on 1-4 family residential properties) with a remaining maturity of three months or less (LOO).

Short-Term Liabilities

Trading Liabilities:

- Includes liability for short positions and revaluation losses on interest rate, foreign exchange rate, and other commodity and equity contracts (TRL)

Federal funds purchased and repurchase agreements:

- Total federal funds purchased and securities sold under agreements to repurchase in domestic offices (FRP).

Foreign deposits (with a maturity of <3 months):

- The sum of all foreign office deposits, including demand deposits, money market deposits, other savings deposits and time deposits (DEF).

Deposits (with a maturity of <3 months):

- Transaction Accounts: The sum of the following accounts held in domestic offices: demand deposits, NOW accounts, Automated Transfer Service accounts and telephone or preauthorized transfer accounts (TRX).

Non-Transaction Accounts (with a maturity of <3 months):

- Total money market deposit accounts held in domestic offices (MMD).

Other savings deposits (excluding MMDAs, with a maturity of <3 months):

- Other savings deposits held in domestic offices, aside from money market deposit accounts (OSD).
- Domestic time deposits of less than $100,000, plus all open-account time deposits that are either fixed rate instruments with remaining maturities of 3 months or less or floating rate instruments subject to repricing on a quarterly or more frequent basis (TDS).
- Domestic time deposits of $100,000 or more which are either fixed rate instruments with remaining maturities of 3 months or less or floating rate instruments subject to repricing on a quarterly or more frequent basis (TDL).

Table 6-4: Descriptive Statistics of the Data Sample

This table presents the average development of the balance sheet composition of banks that failed (F) in the course of our sample and banks that did not fail (NF). The table shows the share of liquidity-relevant assets (LR-Assets), liquidity-relevant liabilities (LR-Liabilities) and equity in relation to the balance sheet total. Median and mean values are presented. The data contains quarterly reports of US-American banks to the FDIC for the period 2001 to H1-2010. The values are reported as of end-of-year.

	Share of Balance Sheet Total Median						Share of Balance Sheet Total Mean					
Year	LR-Assets NF	*LR-Assets F*	LR-Liabilities NF	*LR-Liabilities F*	Equity NF	*Equity F*	LR-Assets NF	*LR-Assets F*	LR-Liabilities NF	*LR-Liabilities F*	Equity NF	*Equity F*
2001	42.9%	*41.2%*	56.1%	*53.6%*	9.5%	*8.6%*	42.7%	*40.7%*	55.5%	*51.2%*	11.2%	*10.7%*
2002	42.6%	*39.6%*	56.1%	*51.1%*	9.7%	*8.8%*	42.6%	*38.7%*	55.5%	*49.9%*	11.4%	*10.3%*
2003	42.6%	*37.0%*	57.3%	*50.8%*	9.7%	*8.8%*	42.5%	*38.3%*	56.6%	*49.8%*	11.4%	*11.0%*
2004	44.4%	*46.3%*	56.5%	*49.4%*	9.8%	*9.2%*	43.9%	*44.9%*	55.4%	*49.1%*	11.6%	*11.7%*
2005	44.5%	*52.7%*	54.8%	*47.5%*	9.8%	*9.1%*	44.3%	*47.9%*	54.0%	*46.6%*	11.9%	*11.4%*
2006	43.7%	*53.7%*	53.5%	*44.4%*	10.0%	*9.2%*	43.5%	*48.6%*	52.7%	*44.7%*	12.4%	*11.3%*
2007	41.8%	*47.6%*	53.6%	*43.7%*	10.3%	*8.9%*	41.7%	*44.4%*	52.3%	*43.4%*	12.8%	*10.0%*
2008	35.1%	*34.6%*	52.9%	*38.9%*	10.0%	*6.7%*	36.3%	*34.2%*	51.8%	*40.1%*	11.9%	*6.6%*
2009	33.7%	29.1%	54.8%	41.9%	9.9%	3.2%	35.4%	*30.4%*	53.5%	*41.8%*	11.3%	*3.1%*
H1 - 2010	34.4%	30.1%	54.2%	38.1%	10.0%	2.0%	35.8%	*30.0%*	53.1%	*38.6%*	11.2%	*1.6%*
Total	40.7%	41.4%	55.1%	46.2%	9.9%	8.6%	41.0%	*41.3%*	54.1%	*46.0%*	11.8%	*10.02%*

6.4. Empirical Results

6.4.1. Analysing Liquidity-Relevant Assets and Liabilities

We start our empirical analysis by focusing on liquid assets and liquid liabilities on the banks' balance sheets. Figure 6-1 and Figure 6-2 show the median values of the different liquidity-relevant balance sheet items in relation to the respective balance sheet total.[41] The axes of the figures are kept constant to illustrate the relative importance of the different balance sheet items.

Starting with the assets plotted in Figure 6-1, we observe that even though the positions are fairly comparable for failed and non-failed banks, there is an outstanding exception to be noted, namely net other loans and leases. This balance sheet position consists of unsecured short-term loans and hence the risky part of the entire loan portfolio on the balance sheet. The graph shows a bell-shaped development on its path towards default with failed banks starting at a higher level. The failed banks build up a short-term position in loans of slightly above 30% of the balance sheet total approximately two years before default as opposed to fairly stable positions at non-failed banks, even though the position slightly mimics the bell-shape of the failed sample. In the advent of default failed banks accumulate a higher level of cash, whereas in earlier periods, cash holdings are constantly lower for the sample of failing banks. Hording of liquidity just prior to a default situation is less surprising, since the failed banks need to show market participants alleged capital strength in order to prevent a bank run.

[41] Any balance sheet positions with median values that are mostly zero are excluded from detailed consideration.

Figure 6-1: Median of Liquidity-Relevant Balance Sheet Items to Balance Sheet Total, Asset-Side

This figure presents the median evolution of the liquidity-relevant balance sheet positions on the asset-side for failed banks and non-failed bank separately. For the failed banks, period 0 corresponds to the last available data before default. Non-failed banks are ordered accordingly to reflect the default pattern of failing banks and hence control for any industry-wide developments. Any short-term asset positions with a median of zero in all quarters are not included in the figure. All values are calculated in relation to the balance sheet total.

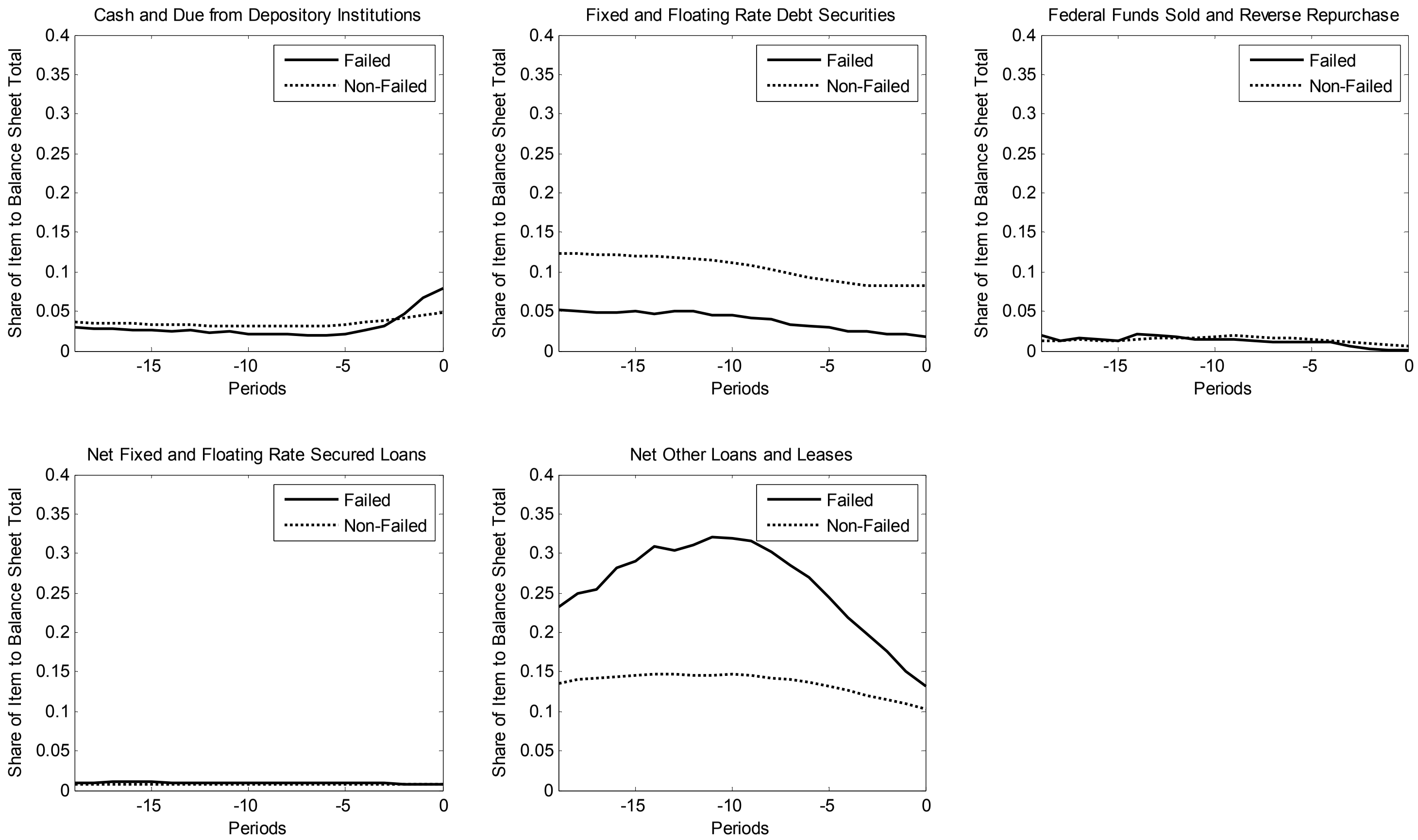
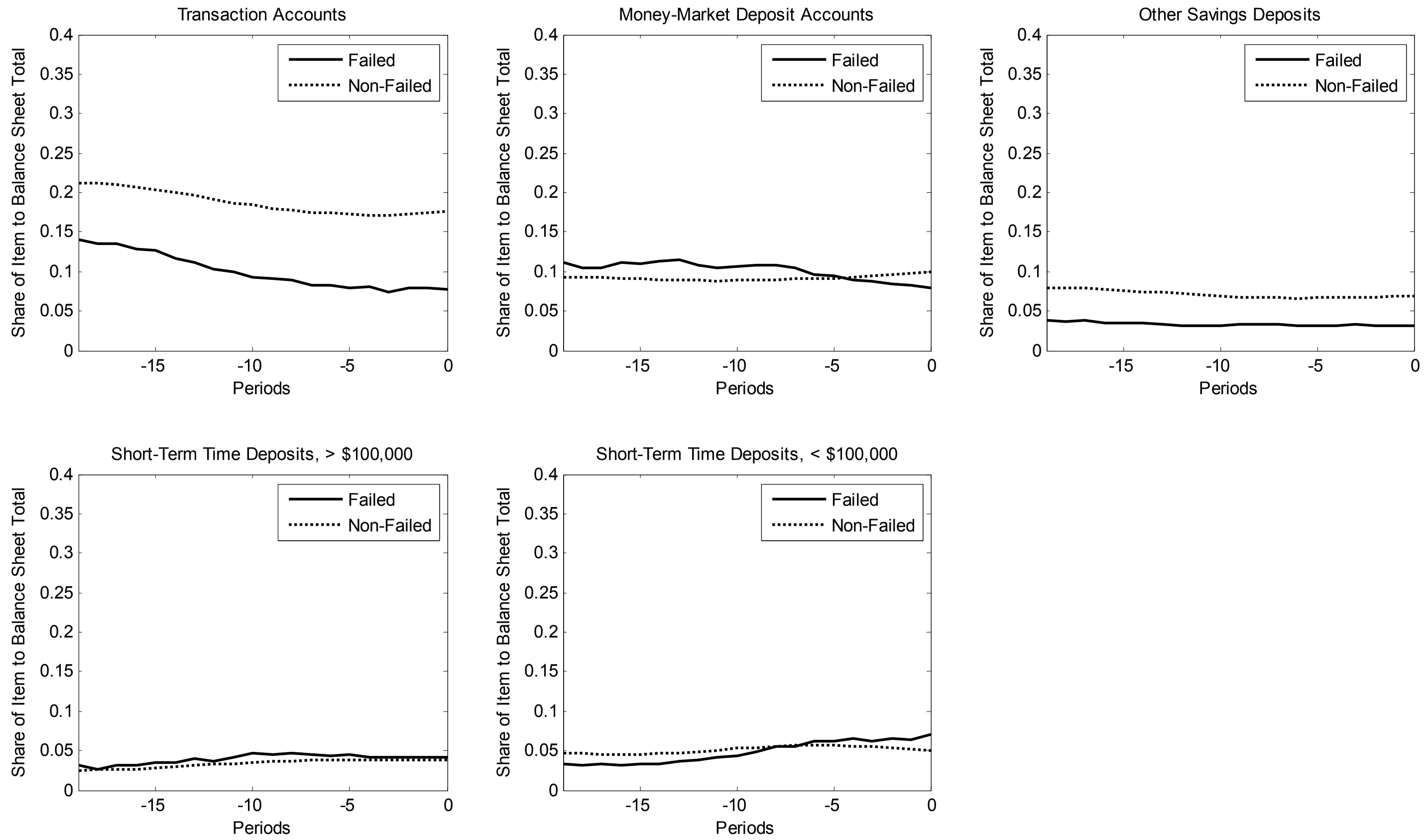


Figure 6-2: Median of Liquidity-Relevant Balance Sheet Items to Balance Sheet Total, Liabilities-Side

This figure presents the median evolution of the liquidity-relevant balance sheet positions on the liabilities-side for failed banks and non-failed bank separately. For the failed banks, period 0 corresponds to the last available data before default. Non-failed banks are ordered accordingly to reflect the default pattern of failing banks and hence control for any industry-wide developments. Any short-term liabilities positions with a median of zero in all quarters are not included in the figure. All values are calculated in relation to the balance sheet total.



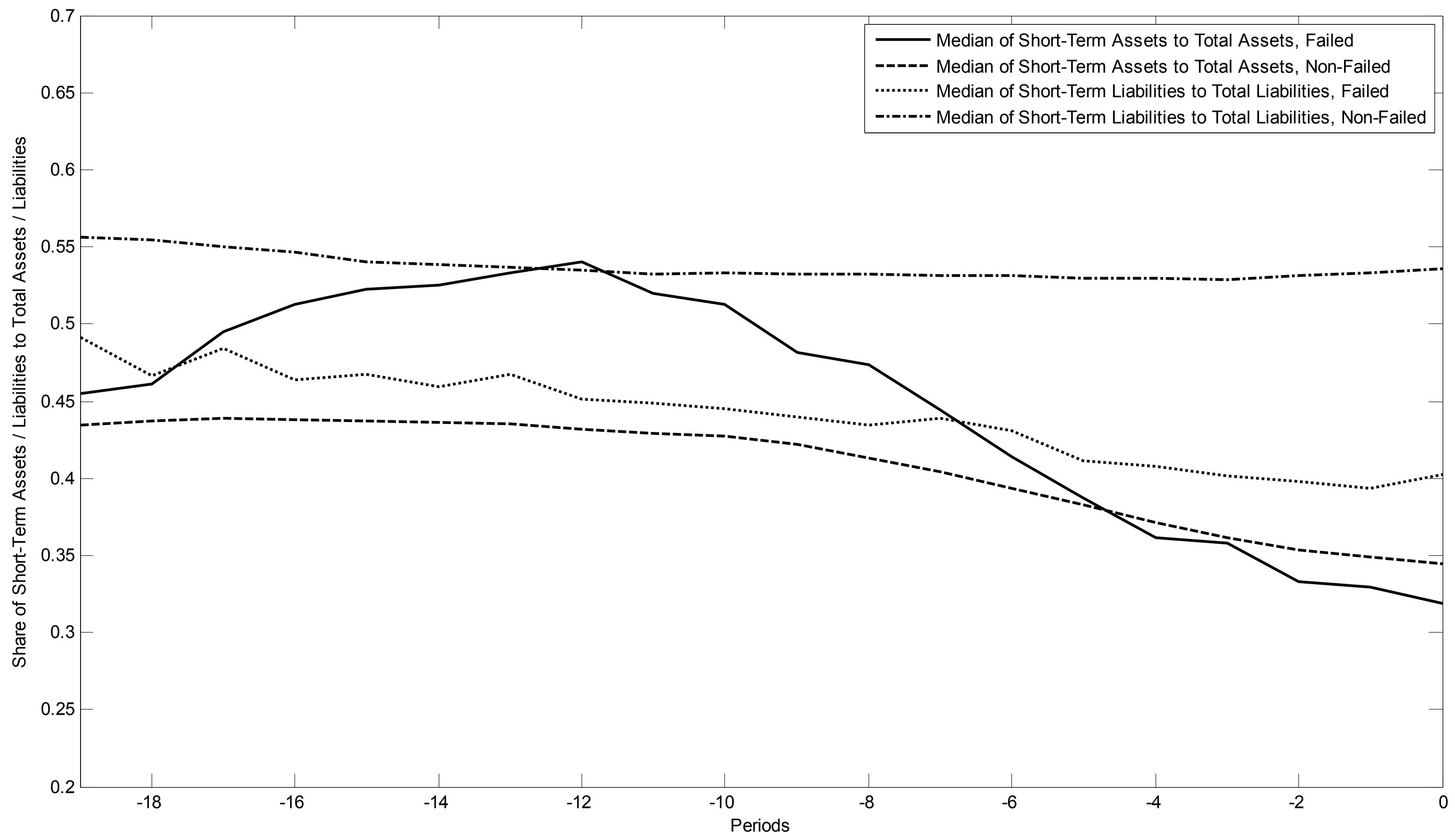
In general, with regard to liquid liabilities as shown in Figure 6-2, the detailed plots are fairly comparable for the failed and the non-failed banking group. However, there is one interesting and substantial difference in the transaction accounts to be noted: these positions start from rather similar levels for the failed and the non-failed sample and then diverge due to the strong decrease of transaction accounts of the failed sample. This decrease is also the only non-constant movement of any of the individual balance sheet positions. Large short-term time deposits are almost identical for the failed and the non-failed banks throughout the whole period at stable values. Money-market accounts are slightly higher on a rather constant level for the failed sample, whereas in the last two quarters prior to the default point the failed banks lose them proportionally to the surviving peers as a refinancing source. The small short-term time deposits are slightly smaller for the failed sample but the difference is negligible. Only in the last two to four quarters are failed banks able to attract more short-term time deposits below $100,000, which is particularly interesting since this deposit accounts are fully secured by the FDIC in case of a default. Finally, there is a constant difference of roughly 4% to be identified with regard to other savings deposits, i.e. the non-failing banks constantly show a higher value for this item relative to the balance sheet total. This difference, however, remains stable even in the advent of default.

Figure 6-3 summarizes the development of total liquidity-relevant assets and liabilities (median values) for the two samples of failed and non-failed banks. We conduct the same analysis for mean values which produces similar yet less pronounced results. These are attached in Appendix 6-I for reasons of completeness.

The median values exhibit several interesting patterns: First of all, the values for the non-failed data sample show only little fluctuations over time for both liquidity-relevant assets and liquidity-relevant liabilities. Therefore, we can interpret the non-failing banks as a benchmark to compare the sample of failed banks to. Additionally, the median values of the liquidity-relevant assets of the non-failing banks lie in a range between 34% and 44%, whereas the median values of the liquidity-relevant liabilities vary between 53% and 55% of the balance sheet total. Assuming that the liquid assets and liabilities are, on average, dominated by short-termed balance sheet positions, there exists a substantial mismatch between assets and liabilities. This mismatch, however, establishes what is at the heart of the banking business model, namely positive term transformation and the according interest income.

Figure 6-3: Median of Liquidity-Relevant Assets / Liabilities to Total Balance Sheet Size over Time

This figure presents the median evolution of the liquidity-relevant balance sheet positions for failed banks and non-failed banks separately. For the failed banks, period 0 corresponds to the last available data before default. Non-failed banks are ordered accordingly to reflect the default pattern of failing banks and hence control for any industry-wide developments. The values are calculated in relation to the balance sheet total.



This picture changes completely when looking at the data for failed banks. The figures for both liquidity-relevant assets and liquidity-relevant liabilities differ quite significantly in the level and in their development over time when compared to the non-failed bank sample. The values for liquidity-relevant liabilities decrease more or less monotonically. Starting at roughly 49% of the balance sheet, the values steadily decrease to levels of about 40% when they approach the ultimate default date.

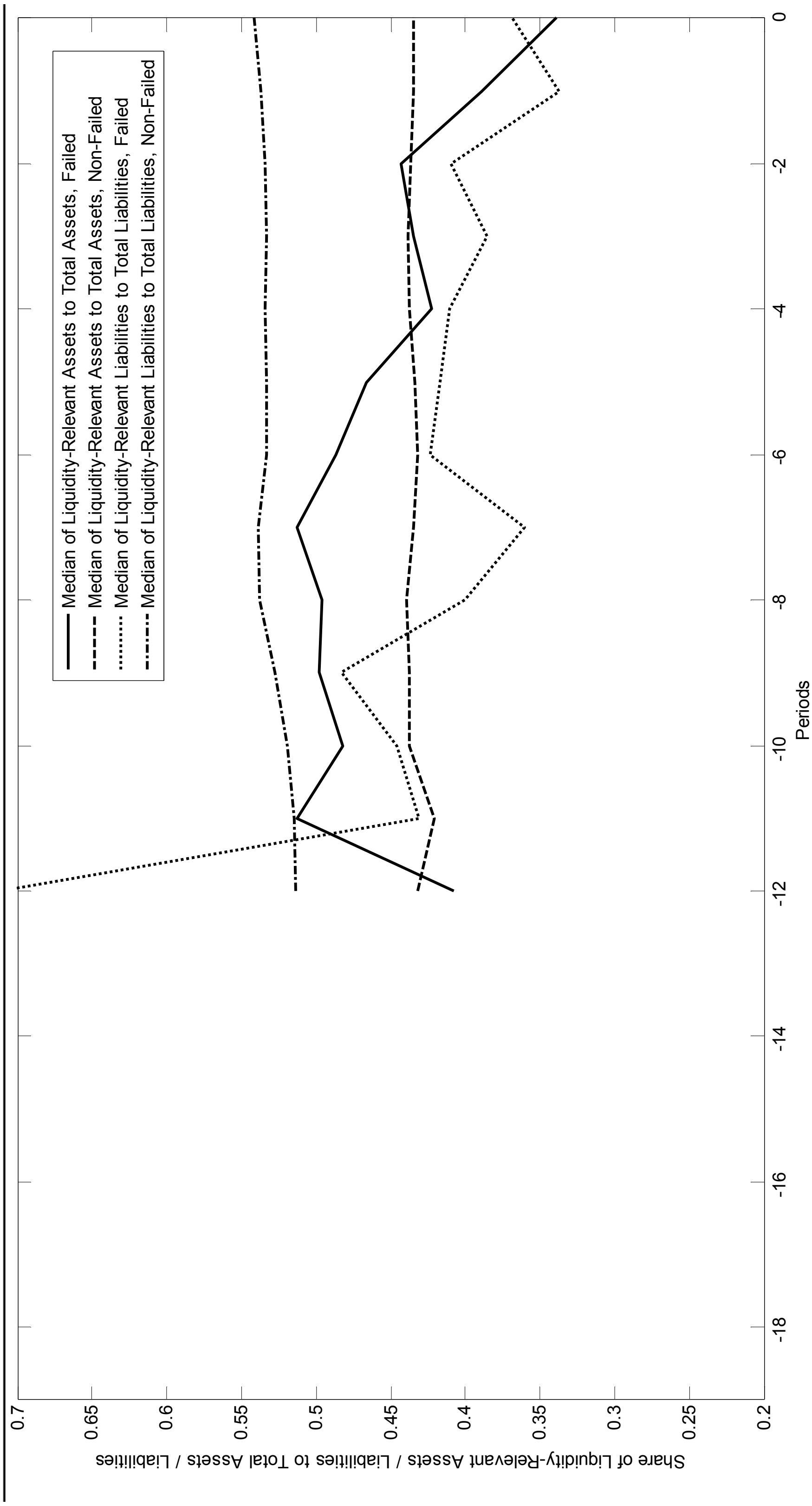
The liquidity-relevant assets for the failed group exhibit a non-monotonic pattern throughout the time series. Starting from values in the range of 45% about five years before the default date, the liquidity-relevant asset ratio starts to increase to maximum values of about 54% two and a half years before default. From this maximum, the values then change their inherent patterns and decrease monotonically to values of about 33%. However, some part of this final decrease in liquidity-relevant assets has to be accounted to industry dynamics, as also the non-failing sample shows a slow decrease in the same periods. Following our interpretation, the pattern observed for the failing sample might be interpreted as a deviation from the traditional term transformation approach – especially when benchmarked with the non-failing bank sample.

Since our sample is strongly biased towards defaults resulting from the recent financial crisis, we include, as a robustness check, an analysis of these results with the defaulting banks of the years prior to 2006. Besides the events of the financial crisis we also want to control our results for different yield curve structures occurring during our analyzed time period. This sample amounts to a total of 22 bank defaults, with the last failure dating back to June 2006. Accordingly, the longest history in our data sample of the pre-crisis failures is restricted to 13 quarters.

Figure 6-4 shows the results of this analysis. The median values show a larger degree of statistically driven variability due to the much smaller sample size. The trend, however, confirms the findings of the overall sample. Adjusting for the lack of previous periods and the higher degree of variability, the developments of both, liquidity-relevant assets and liabilities seem to exhibit a similar pattern in the pre-crisis sample than in the overall sample. Short-term liabilities decrease steadily in the advent of default and short-term assets show the same hump-shaped development as in Figure 6-3. Summing up, these results suggest that the development of liquidity-relevant balance sheet positions seems to be robust over time and is not biased by specific features of the current financial crisis or a specific interest rate environment.

Figure 6-4: **Median of Liquidity-Relevant Assets / Liabilities to Total Balance Sheet Size, Pre-Crisis Sample.**

This figure presents the median evolution of the liquidity-relevant balance sheet positions for failed banks and non-failed bank separately. The failed banks sample only includes institutions that failed prior to 2007, which we set as the beginning of the recent financial crisis. For the failed banks, period 0 corresponds to the last available data before default. Non-failed banks are ordered accordingly to reflect the default pattern of failing banks and hence control for any industry-wide developments. The values are calculated in relation to the balance sheet total. Since there were no defaults in years directly preceding the crisis, this sample contains only few observations.



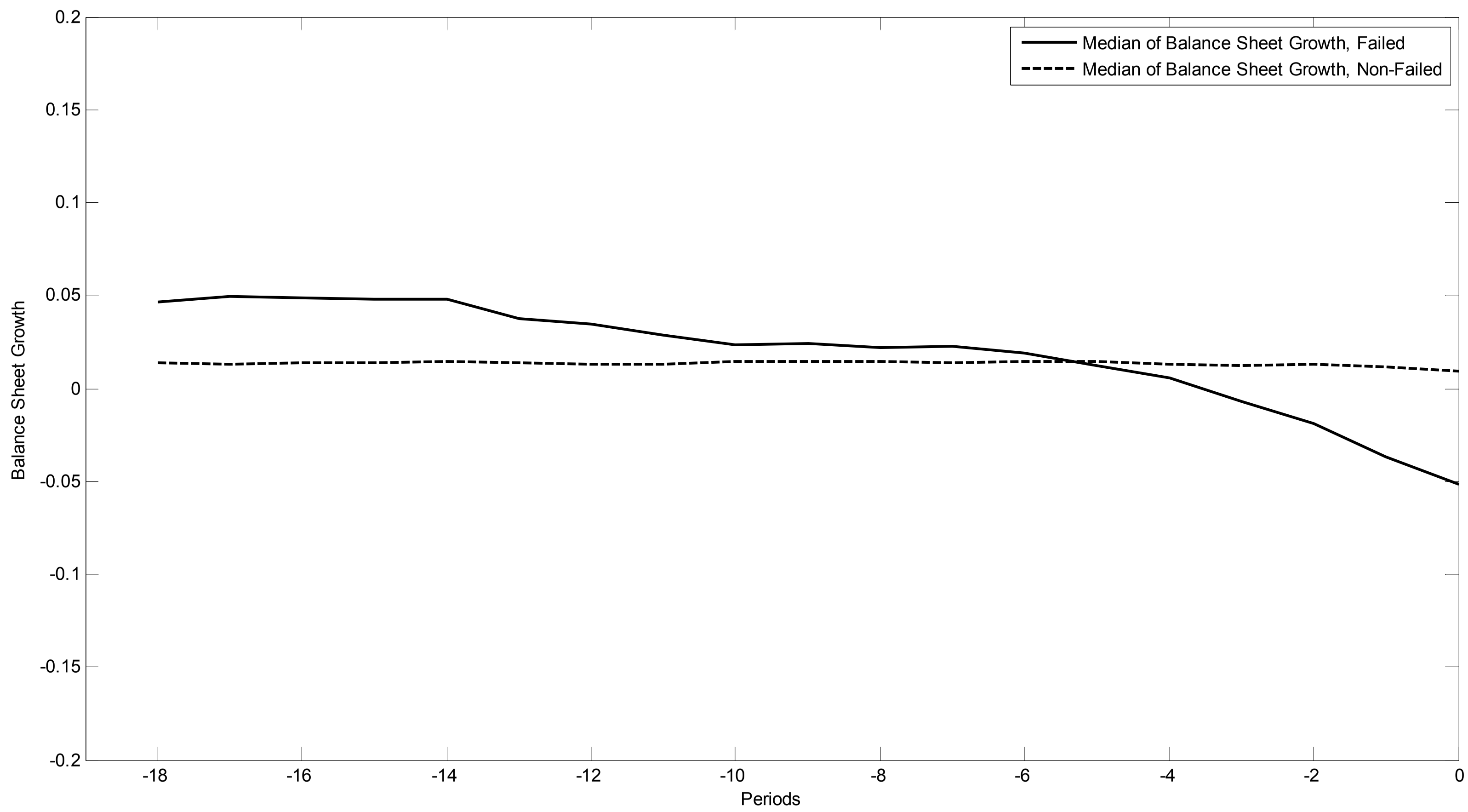
The analysis above was entirely based on analyzing ratios, e.g. individual balance sheet items in relation to the overall balance sheet. To fully understand and interpret the differences in the liquidity structure, we looked at the median growth of liquidity-relevant balance sheet items (assets and liabilities). The detailed analysis can be found in Appendix 6-II and Appendix 6-III and shows that over the entire sample of failed banks, volatility with regard to individual balance sheet items is much more pronounced than it is for the non-failing banks. Most of the figures, however, circle around zero values for both groups, indicating no relevant changes in patterns. Net Other Loans and Leases establish the exception and are the main driver of the overall development compared to the findings of Figure 6-5 (median growth of balance sheet total). It becomes obvious that the failed bank sample grows at a higher pace with regard to absolute balance sheet numbers (e.g. driven by Net Other Loans and Leases) than the non-failed banks' balance sheets. This pattern appears up to roughly two years before a default occurs. With regard to our relative analysis of the balance sheet items this means that the increase of liquidity-relevant assets of the failed sample is even more severe as the balance sheet total increased at the same time.

To further analyze the decrease of short-term liabilities and the shift in balance sheet positions, we cross-checked for the medians of illiquid balance sheet items to balance sheet totals on the asset and the liability side. It becomes clear that the increase in liquidity-relevant loans and leases in the failed banking group is achieved by a decrease in all other long-term loans and leases (see Appendix 6-IV and Appendix 6-V). With regard to the liability side, it is remarkable that about one year before default, long-term time deposits smaller than USD 100,000 increase sharply for the failed banking sample. Furthermore, the large long-term deposits above USD 100,000 increase on the path to default and constantly remain at higher levels for the failed banks.

Besides the analysis based on median values presented above, the distributions of liquidity-relevant assets and liquidity-relevant liabilities were additionally tested on significant differences between the failing sample and the surviving sample using a two-sample t-test. The results are reported in Appendix 6-I and strongly correspond to the findings of Figure 6-3 with higher differences between the failed and the non-failed sample resulting in higher significance of the tests.

Figure 6-5: Median Growth of Balance Sheet Total

This figure presents the median growth of the balance sheet total for the sample of failed banks and the sample of non-failed banks separately. For the failed banks, period 0 corresponds to the last available data before default. Non-failed banks are ordered accordingly to reflect the default pattern of failing banks and hence control for any industry-wide developments.



6.4.2. Causes for Changes in Liquidity Patterns

Throughout the previous section we observed diverging patterns regarding the liquidity structure of failed and non-failed banks. Since the alteration does not seem to improve the state of banks, this part of the paper aims to identify the reasons for the change in the liquidity positions as undertaken by the failed banks prior to their default. Based on existing literature, we identify two potential motivations that might cause the observed deviations: Window dressing, and a bad client structure.

Regarding window dressing activities, we test for two different hypotheses: First, banks with a more powerful base of creditors might be forced to pursue less aggressive business strategies. In particular we argue that the share of market funding via bonds, as compared to customer deposits, forces a bank to build on a conservative term transforming strategy. This hypothesis is derived from recent work by King and Wen (2011) with regard to the relation between the overall corporate governance structure and managerial risk-taking behavior. The authors find that the overall governance structure has a significant impact on how managers make decisions on investment policy; in particular strong bondholder governance motivates more low-risk investments. Second, with regard to window dressing activities, we test for the share of money market refinancing in relation to deposits. The reasoning is basically identical to the reasoning for bondholders. There are, however, some obvious differences between bondholders and money market refinancing. We argue that the most important difference is that money market refinancing, due to its short maturity, focuses on the short-term liquidity of the creditor – which is in this case the bank. Bondholders, on the contrary, should focus on the longer-term solvency and soundness of a bank since bonds have, on average, a longer maturity. In terms of maturity structure, bondholders are subordinated to money market investors and thus care, in terms of governance, more about the longer-term solvency.

Table 6-5: Diff-in-Diff Test on Share of Bondholders

This table presents the results of the difference-in-differences test on the change in liquidity-relevant assets in the period 19 to 12 quarters before default. The test uses a median-split based on the share of bondholders of banks and a distinction of failed and non-failed banks. The significance of differences in changes of liquidity-relevant assets is tested using a two-sample t-test; the difference in differences is tested using a F-test. The results show whether a different level of bondholders in the refinancing structure induces the changes in the liquidity structure of banks.

Difference t = -19 to t = -12

	Failed	Non-Failed	Diff / **Diff-in-Diff**
	Change in Share of Liquid Assets		
High Level of Bondholders	0.111	0.002	0.1095***
Low Level of Bondholders	0.031	-0.062	0.0931***
Diff / **Diff-in-diff**	0.0799***	0.0635***	**0.016**

//*** indicate significance on the 10%/5%/1%-level.*

Table 6-6: Diff-in-Diff Test on Share of Money Market Refinancing

This table presents the results of the difference-in-differences test on the change in liquidity-relevant assets in the period 19 to 12 quarters before default. The test uses a median-split based on the share of money market refinancing of banks and a distinction of failed and non-failed banks. The significance of differences in changes of liquidity-relevant assets is tested using a two-sample t-test; the difference in differences is tested using a F-test. The results show whether a different level of moneymarket refinancing induces the changes in the liquidity structure of banks.

Difference t = -19 to t = -12

	Failed	Non-Failed	Diff / **Diff-in-Diff**
	Change in Share of Liquid Assets		
High Moneymarket Ref.	0.110	-0.011	0.121***
Low Moneymarket Ref.	0.032	-0.043	0.075***
Diff / **Diff-in-diff**	0.078***	0.032***	0.046**

//*** indicate significance on the 10%/5%/1%-level.*

We test these hypotheses using a median split of the failed and the non-failed sample and a difference-in-differences approach. The median split is based on the share of bondholders in Table 6-5 and based on the share of money market refinancing in Table 6-6. This results in four subsamples for each of the two splitting factors. According to our findings in Figure 6-3, we focus on the period four to five years prior to default, which corresponds to the time frame in which the banks most strongly increase their LRA. We employ a difference-in-differences approach to test whether the increase in LRA is significantly different between the high level of bondholders (money market funding activities) and the low level of bondholders (money market funding activities) groups. The results show that in both, the failed and the non-failed sample, banks with a higher share of bondholders increased the LRA to a significantly greater extent (or decreased less) than the banks with a low share of bondholders. This is in line with expectations if bondholders did in fact foster window dressing activities. The difference-in-differences, however, is not statistically significant, indicating that the impact of a higher share of bondholders is similar for the failed and the non-failed sample. This does not support the hypothesis that bondholders have an impact on changes in LRA, since the effect is only observable in the failed sample and hence, the differences should be more pronounced here. We therefore infer that there is only weak indication for window dressing behavior with regard to bondholders.

The results on money market refinancing are qualitatively similar to the results on bondholders. Regarding the failed sample, the figures on the high and the low money market group are almost identical to the figures with the bondholder split. However, since the difference in the non-failed sample is less pronounced for the money market case, we find a higher and statistically significant difference-in-difference for the case of money market refinancing. Following the outlined argumentation, it makes sense that the observed effect is more pronounced: Since the observed increase in LRA is mostly due to an increase in unsecured, short-term loans, it is reasonable to argue that banks that are strongly financed by short-term oriented money market funds, have a higher incentive to improve the liquidity position of the bank. Regarding bondholders, this effect is less pronounced since bondholders not only focus on the short-term liquidity of banks, but they also focus on low credit standards associated with short-term unsecured loans.

In the next step, we test for a bad client base of banks. The reasoning is that banks that initially have a worse client base will be facing a higher amount of unused commitments that are called in the case of an economic crisis. This could also have happened during the recent crisis, when bad borrowers were forced to draw on their credit lines, either because they needed additional financing or because the existing financing was not extended. Accordingly, in this scenario, a bank with a higher amount of outstanding unused commitments would face a stronger increase in LRA. In this context the shift in its liquid assets would not be induced by a voluntary immediate management decision but an exogenous event forcing the bank to diverge from the existing liquidity structure. The results on the difference-in-differences test support the hypothesis of unused commitments as a driver of the observed changes in the balance sheet structures: We find that banks with a higher amount of unused commitments face a stronger increase in LRA throughout the observation period in the failed sample as well as in the non-failed sample. We additionally find that this effect is more pronounced for the failed banks, which is in line with the findings of Figure 6-3.

Table 6-7: Diff-in-Diff Test on Unused Commitments

This table presents the results of the difference-in-differences test on the change in liquidity-relevant assets in the period 19 to 12 quarters before default. The test uses a median-split based on the unused loan commitments of banks and a distinction of failed and non-failed banks. The significance of differences in changes of liquidity-relevant assets is tested using a two-sample t-test; the difference in differences is tested using a F-test. The results show whether a different level of unused commitments to customers' credit lines induces the changes in the liquidity structure of banks.

Difference t = -19 to t = -12

	Failed	Non-Failed	Diff / **Diff-in-Diff**
	Change in Share of Liquid Assets		
High Unused Commitments	0.109	-0.011	0.12***
Low Unused Commitments	0.032	-0.043	0.075***
Diff / **Diff-in-diff**	0.077***	0.032***	**0.045****

//*** indicate significance on the 10%/5%/1%-level.*

We also control our empirical findings with regard to different levels of leverage (defined as equity to total assets) and analyse if the individual level of bank leverage has an impact on the observed shift in liquidity patterns. Again, we apply a difference-in-differences approach to test whether the increase in LRA is significantly different between the high-leverage and the low-leverage groups for the same time period as used throughout Tables 6-5 to 6-7.

Table 6-8: Diff-in-Diff Test on Leverage

This table presents the results of the difference-in-differences test on the change in liquidity-relevant assets in the period 19 to 12 quarters before default. The test uses a median-split based on the leverage ratio of banks and a distinction of failed and non-failed banks. The significance of differences in changes of liquidity-relevant assets is tested using a two-sample t-test; the difference in differences is tested using a F-test. The results show whether a different level of leverage induces the changes in the liquidity structure of banks.

Difference t = -19 to t = -12

	Failed	Non-Failed	Diff / **Diff-in-Diff**
	Change in Share of Liquid Assets		
High Leverage	0.029	-0.053	0.082***
Low Leverage	0.112	-0.004	0.116***
Diff / **Diff-in-diff**	-0.083***	-0.049***	**-0.034**

//*** indicate significance on the 10%/5%/1%-level.*

Table 6-8 shows the test results for the leverage factor. We find that both, the failing and the non-failing banks increased their LRA less during the observation period, if the banks were more leveraged. The difference-in-differences supports this finding as it is negative and not statistically significant. In case of a causal relationship, we would expect to find a more pronounced, positive difference in the failed sample as compared to the non-failed sample. We also controlled for potential lag effects based on past realized losses prior to the liquidity shift as well as regressed past earnings on the corresponding banks liquidity strategy, which also led to now significant results. Thus, the banks' leverage factor can be excluded as a cause for the observed change in liquidity patterns.

Summing up, we conclude that a bad client base forced banks to increase their LRA due to outstanding commitments that were eventually drawn in the course of the crisis. Additionally, also window dressing activities appear to play an important role.

We show that the management of banks tries to appear exceptionally liquid towards outside investors. This is especially true with regard to short-term money market funds, but less so with regard to bondholders. Finally, leverage seems not to be an important factor in this scenario.

6.4.3. Impact of Liquidity on Bank Stability

In a third step, we want to enrich our analysis by showing how liquid assets and liabilities of banks might be used in assessing bank stability and predicting bank defaults. Therefore, we perform two sets of logistic regressions on our data sample as a follow-up to the previous analyses. Both sets employ bank failure as dependent variable and liquidity-relevant assets and liquidity-relevant liabilities as predictor variables. Additionally, based on existing financial literature we include several control variables (Cole and Gunther 1995 and 1998, Wheelock and Wilson 2000, Arena 2008):

Equity serves as a security cushion in case of unfavorable market developments and therefore enhances a bank's ability to absorb shocks and remain adequately capitalized even in distress. Accordingly, equity in relation to total assets (EQA) is assumed to positively affect bank stability. Asset quality affects bank soundness by imposing a high risk of losses for future periods. In this area, three different variables were found to significantly influence bank defaults: Loans past due more than 90 days to total assets, non-accruing loans to total assets and total non-performing loans to total assets. As a predictor of future losses, these variables are assumed to negatively affect bank stability. An additional fourth variable controls for effects of the recent financial crisis and is calculated as real estate owned by the financial institution relative to the balance sheet total (ORE). We measure profitability using the net income of banks to balance sheet total (INC). As profitable banks should be more capable of dealing with negative external shocks, a higher net income ratio should decrease the risk of failure. The measures regarding liquidity are investment securities to total assets (SCA) and large certificates of deposits to total assets (LCD). These measures approximate liquid assets and stable liabilities respectively and are hence assumed to foster bank stability. Additionally, we control for unused loan commitments of banks relative to their balance sheet total (UCA). During a period of crisis, contractually binding loan commitments are more likely to be drawn and hence, a higher degree of unused commitments makes a bank more vulnerable (Campello et al. 2010). Based on recent research of Lepetit et al. (2008), we also control for the impact of income diversification using the share of non-interest income to total income (DIV). Finally, we control for any size effects using the natural logarithm of the balance sheet total (SIZ) and different bank types using a dummy variable for commercial banks and savings banks (TYP).

Before conducting the logistic regressions, we test all variables on multi co-linearity using the variance inflation factor. The results suggest high co-linearity among all variables on loan quality. Consequently, we use principle factor analysis to combine the information in one variable. The resulting variable (BAD) still accounts for 85.5% of the total variance. The new set of variables is no longer subject to co-linearity.

We conduct the first analysis as pooled logistic regression using all available cases and all periods (Table 6-9). The analysis of the constrained model includes only the control variables; the unconstrained model includes also the liquidity-relevant assets and liabilities. For both, the constrained and the unconstrained model, all variables except for income diversification proof to significantly affect bank default. This finding is interesting in the light of the large body of current literature dealing with this topic that finds a positive influence of income diversification on bank stability, e.g. Lepetit et al. (2008) and Demirgüç-Kunt and Huizinga (2010). We in contrast find that income diversification does not impact the likelihood of bank failure in any direction. The level of net income, however, does significantly affect bank stability. Regarding the other significant control variables, a bank is more likely to fail if it is larger, has more unused commitments outstanding, less equity and more non-performing loans. These findings are all in concordance with our expectations and the results of previous studies. A higher degree of liquid securities increases bank stability while large deposits decrease stability. This is also in accordance with expectations since trading securities are more easily sold and turned into cash in case of distress. Our results suggest a higher risk of default for savings banks as compared to commercial banks. The constrained model explains 21.3% of the overall variance, based on the adjusted McFadden's R-squared, which seems realistic as most of these measures were designed to predict bank default in the short run.

Table 6-9: Pooled Logistic Regression

This table presents the results of the logistic regression using liquidity-relevant assets (LRA) and liquidity-relevant liabilities (LRL) on failure of banking institutions. As control variables we employ the log of the balance sheet total (SIZ), a dummy variable indicating the bank type (TYP), a proxy of the bank's income diversification (DIV), unused commitments in relation to total assets (UCA), equity to balance sheet total (EQA), real estate owned to balance sheet total (ORE), securities to balance sheet total (SCA), large certificates of deposits to balance sheet total (LCD), net income to total assets (INC) and one variable reflecting the amount of bad loans in relation to balance sheet total (BAD). We conduct a logistic regression for the unconstrained model, which includes all of the variables and for the constrained model which only employs the control variables, excluding LRA and LRL. The likelihood-ratio test indicates whether the improvement of the model fit by including LRA and LRL is statistically significant.

Dependent:	Failure			
	Unconstrained Model		Constrained Model	
Independent	Exp(Coeff)	Coeff / Std. Err	ExpCoeff	Coeff / Std. Err.
LRA	6.66	1.896***		
		[0.521]		
LRL	0.09	-2.417***		
		[0.556]		
SIZ	1.14	0.135***	1.13	0.121**
		[0.0499]		[0.0506]
TYP	1.41	0.344	1.53	0.428**
		[0.249]		[0.172]
UCA	22.85	3.129***	37.94	3.636***
		[0.686]		[0.677]
EQA	0.00	-9.607***	0.00	-7.622***
		[1.688]		[1.649]
BAD	2.97	1.090***	3.20	1.164***
		[0.0909]		[0.0891]
ORE	0.00	-12.17	0.00	-11.37
		[12.14]		[12.02]
SCA	0.07	-2.693***	0.06	-2.857***
		[0.693]		[0.704]
LCD	83.43	4.424***	269.89	5.598***
		[0.746]		[0.711]
INC	28.50	3.350***	11.20	2.416***
		[0.748]		[0.721]
DIV	0.99	-0.0111	1.00	-0.00952
		[0.0149]		[0.0144]
Observations	10,966		10,966	
Prob > Chi2	0.000		0.000	
McFadden's Adj. R-Squared	0.222		0.213	
Likelihood-ratio Test				
LR Chi2(2)	23.81			
Prob > Chi2	0.000			

** indicates significance on the 10%-level.*

*** indicates significance on the 5%-level.*

**** indicates significance on the 1%-level.*

The unconstrained model incorporates liquidity-relevant assets and short-term liabilities as additional predictors. Both variables significantly contribute to the performance of the model. The adjusted McFadden's R-squared of the model is 22.2%, which suggests an improvement in predictive power even when adjusting for the additional variables included. To test this improvement on statistical significance, we used the likelihood-ratio test comparing the unconstrained and the constrained model. The null hypothesis has to be rejected at the 0.1% significance level and, hence, omitting LRA and LRL as predictors significantly decreases the model fit.

The coefficients of the analysis suggest that a higher portion of liquidity-relevant assets increase the likelihood of default and increasing liquidity-relevant liabilities enhance bank stability. This finding is in contrast to the common understanding of liquidity deficits as a major driver of bank default. To understand these results, it is important to keep in mind that we employed the analysis on a medium to long-term horizon as compared to most other studies. Consequently, it seems that, even though liquidity is unarguably important for the survival of a financial institution in the very short run, keeping the balance sheet more liquid in terms of matching maturities of the assets and the liabilities, impacts bank stability to the negative in the medium to long-run. These findings can be linked to the displayed positive correlation between profitability and bank stability: In a normal interest environment liquid assets yield lower income as compared to long-term assets.

To further analyze this finding, we conduct a second set of logistic regressions (Table 6-10). This time, the failed sample is split up according to remaining quarters to default and each of these subsamples is compared to all non-failing cases and periods.[42] We again, conduct the analysis for the constrained model, using only the control variables, and the unconstrained model, which also includes liquidity-relevant assets and liquidity-relevant liabilities. The results of the control variables are not reported, but the main aspects for the control variables match with the results from the pooled regression. In both cases, failure is the dependent variable.

The results of this analysis match very well with the findings of Figure 6-3. The variance explained in the first half of the sample is relatively low. This is probably due to the fact that the control variables focus on short-term default and hence do a bad job

[42] All non-failing cases and periods are included since there is no single quarter, meaningfully corresponding to the default date of the failing banks.

predicting default up to five years in advance. However, it is worthwhile noting that the small amount of explained variance during these periods is strongly influenced by liquidity-relevant assets and liquidity-relevant liabilities. These structural differences seem to significantly contribute to the model fit even in the very long run. This fact is supported by the 0.1%-significance of liquidity-relevant liabilities in all of these periods and also the likelihood-ratio test which supports the assumption of significant model improvement by the two predictor variables for all periods.

Table 6-10: Logistic Regression, Failed Institutions by Quarter

This table presents the results of logistic regressions with liquidity-relevant assets (LRA), liquidity-relevant liabilities (LRL) and a set of control variables as predictors and failure as dependent variable. We conduct the analysis based on quarters-to-default of the failed sample. In every quarter, only the respective values of the failed samples are included. Quarter t = -19 corresponds to the report five years prior to default. Quarter t = 0 represents the last available report prior to default. For the non-failing sample, the data is weighted matching the default pattern of the failing sample. The McFadden's adjusted r-squared are reported for the constrained model, which includes only control variables and the unconstrained model including also LRA and LRL as predictors. Additionally, the results of the likelihood-ratio test of the constrained and unconstrained model are reported.

Dependent: Failure

	Exp(Coeff)		z-Value			McFadden's Adj. R-Squared		Likelihood-Ratio Test	
Independent	LRA	LRL	LRA	LRL	Prob > Chi2	Unconstrained	Constrained	LR Chi2(2)	Prob > Chi2
t = -19	4.93	0.25	4.23***	-3.34***	0.00	0.054	0.050	22.98	0.00
t = -18	6.38	0.18	5.05***	-4.22***	0.00	0.061	0.054	34.11	0.00
t = -17	8.61	0.19	6.06***	-4.14***	0.00	0.074	0.066	42.64	0.00
t = -16	12.03	0.11	7.28***	-5.68***	0.00	0.091	0.077	66.91	0.00
t = -15	11.23	0.09	7.14***	-6.11***	0.00	0.100	0.086	69.39	0.00
t = -14	14.00	0.08	8.01***	-6.34***	0.00	0.109	0.092	81.90	0.00
t = -13	15.18	0.09	8.30***	-6.22***	0.00	0.108	0.091	84.44	0.00
t = -12	16.89	0.07	8.81***	-7.07***	0.00	0.111	0.090	100.48	0.00
t = -11	14.47	0.06	8.30***	-7.34***	0.00	0.113	0.093	97.05	0.00
t = -10	12.47	0.07	7.73***	-6.96***	0.00	0.107	0.089	85.77	0.00
t = -9	8.95	0.07	6.64***	-6.87***	0.00	0.106	0.091	73.45	0.00
t = -8	7.96	0.05	6.22***	-7.69***	0.00	0.106	0.090	79.77	0.00
t = -7	7.26	0.04	5.89***	-8.28***	0.00	0.111	0.094	85.25	0.00
t = -6	5.16	0.04	4.69***	-7.69***	0.00	0.124	0.111	68.11	0.00
t = -5	2.89	0.05	2.84***	-7.21***	0.00	0.157	0.147	53.16	0.00
t = -4	2.10	0.05	1.87*	-6.72***	0.00	0.214	0.206	44.91	0.00
t = -3	2.57	0.04	2.41**	-7.7***	0.00	0.275	0.265	49.25	0.00
t = -2	3.70	0.03	3.87***	-9.29***	0.00	0.290	0.254	175.32	0.00
t = -1	1.98	0.19	1.41	-3.28***	0.00	0.555	0.553	13.13	0.00
t = 0	1.99	0.57	1.24	-0.92	0.00	0.709	0.707	10.13	0.01

** indicates significance on the 10%-level.*

*** indicates significance on the 5%-level.*

**** indicates significance on the 1%-level.*

The odds-ratio of the liquidity-relevant liabilities remains at relatively constant levels for most of the observation period. Hence, liquidity-relevant liabilities seem to impact the likelihood of failure in a structural sense but do not so much depend on time to default. The impact of liquidity-relevant assets on default probability, however, critically depends on the remaining periods to default. Here, the odds-ratio mimics the hump-shaped development of Figure 6-3. A higher (or lower) difference between the failed and the non-failed sample increases (decreases) the probability of correctly identifying failing institutions. Accordingly, the odds-ratio, or the increase in probability of default due to an incremental increase in the independent variable, ceteris paribus, is larger if the independent variable separates failures from non-failures more sharply.

As with the pooled logistic regression, the range of values of both odds-ratios suggests increasing fragility with lower term transformation for all significant periods. The comparison of the constrained and the unconstrained model shows that our term transformation variables mainly improve the model in the medium term, namely about three to four years before default. This again corresponds to the finding of Figure 6-3, which shows that the dispersion between failed and non-failed liquidity-relevant assets is significant in this period. In particular, the results of the likelihood-ratio test support the findings of the comparison of model fit. All periods show a significant increase in prediction power due to liquidity-relevant assets and liquidity-relevant liabilities.

6.5. Discussion

From the angle of a liquidity-driven perspective, our empirical results suggest that there are distinctive differences between failed and non-failed banks. One of our key findings in this context is that failed banks deviate from their traditional business model and do not continue to perform their original (positive) term transformation function culminating about 3 years before default. During this time period, liquidity-relevant liabilities and liquidity-relevant assets of the failed banks even suggest negative term transformation. This process is largely driven by a shift from long-term loans towards short-term loans and leads to an increase in liquidity. However, this pattern is not persistent until default but is reversed in the last six quarters prior to the default situation. At the same time non-failed banks maintain their original (positive) term transformation and show low volatility in their capital structure. This finding is of particular interest, since term transformation is generally viewed as a bank's (market) risk factor. Yet, in our sample banks actually reducing their term transformation are more likely to default in the intermediate future (2-3 years).

Analysing the reasons leading to the observed shift in liquidity structure we control for window dressing and a bank´s bad client structure. Window dressing proved to be one of the reasons driving the change in liquidity patterns, which is particularly true for money market activities. Banks with a great exposure towards money markets aim to ally their investors with a liquid asset base. This behavior is also reasonable from a governance perspective of money markets investors, since they are among the first to withdraw their money and are therefore particularly concerned about liquidity positions.

As a rather exogenous driven cause, we observed that a bad client base in terms of unused commitments drawn by clients leads to an increase in LRA. We interpret this induced increase as a situation in which banks' clients experience financial difficulties and thus have to rely on their liquidity cushions. Typically prior to a company´s default all existing credit lines are drawn to the maximum. Even though banks cannot avoid these new credit positions, they are the result of former management decisions and banks risk awareness. In this context we also find no empirical prove that leverage ratios are a significant factor driving the documented change in liquidity patterns. A classical moral hazard argumentation is therefore not supported by our results.

About two and a half years before default, counteractions are initiated with the goal of returning to the original term transforming business model. This is tried to be achieved by reducing the risky portion of loans on the balance sheet. During this turnaround process failed banks are not as well positioned as their counterparts with steady business models to absorb potential shocks to the banking business (as experienced throughout the financial crisis). The last quarters before default thus could be interpreted as being dominated by futile counteractions like build-up of cash positions.

The documented shift in liquidity patterns is found for the US banking industry, which is organized as a market-oriented financial intermediation system. The question arising in this context is to what extent our findings also hold for a balance sheet-oriented system. In the following we discuss this issue with regard to the two dominating causes for changes in liquidity patterns: bad client base and window dressing in connection with money market financing.

Table 6-11: Continental European and US Bank Balance Sheet Structure

This table presents the mean relative values of Continental European and US-American balance sheet structures for the financial year 2009. The Continental European sample consists of 4829 banks, whereas the US incorporates 9523 banks. All figures are derived from Bankscope in order to ensure data comparability between the different regions.

Assets (2009, mean values in %)	**Cont. Europe** *(N=4828 Banks)*		**U.S. American** *(N=9523 Banks)*	
Cash & Other Non-Earning Assets	7.7%		*15.8%*	
Total Other Earning Assets	41.7%		*47.8%*	
Equity Investments		*1.8%*		*0.4%*
Other Investments		*0.7%*		*0.8%*
Total Securities		*20.1%*		*14.0%*
Government Securities		*4.6%*		*2.9%*
Due From Banks		*14.5%*		*29.7%*
Total Loans Net	49.7%		35.5%	
Loans to other Corporate		*21.5%*		*3.4%*
Other Loans		*18.1%*		*2.2%*
Mortgages		*10.0%*		*29.9%*
Total Fixed Assets	1.0%		1.0%	

Liabilities (2009, mean values in %)	**Cont. Europe** *(N=4828 Banks)*		**U.S. American** *(N=9523 Banks)*	
Total Deposits	49.8%		43.3%	
Customer & Other Deposits		*31.9%*		*42.7%*
Bank Deposits		*18.0%*		*0.5%*
Total Money Market Funding	16.1%		23.0%	
Securities Loaned		*0.0%*		*7.8%*
Other Securities		*5.8%*		*14.5%*
Other Negotiable Instruments		*10.3%*		*0.7%*
Total Other Funding	27.4%		22.9%	
Total Equity	6.7%		10.8%	

Based on a set of 4,828 Continental European and 9,532 US banks, we outline in Table 6-11 in detail how this system difference leads to heterogeneous balance sheet structures:[43] Primarily, we observe that European banks allocate more assets to their credit book (49.7% versus 35.5%), are less dependent on money market funding activities as compared to their US peers (16.1% versus 23.0%) but rely to a greater extent on deposits (49.8% versus 43.3%) as a refinancing source. US banks in turn allocate more capital to their trading book (47.8% versus 41.7%). We argue that *total net loans* incorporate longer maturity structures on average (and/or are less tradable) as compared to *total other earning assets* and that this difference is not neutralized by significantly shorter maturity structures on the liabilities side of US banks. Therefore, we conclude that term transformation is more accentuated for Continental European than for US banks. Additionally, the Continental European banking system is more oriented towards relationship banking, which results in stable and long-term oriented lending relationships (Ongena and Smith, 2001). In this context, banks are less likely to terminate a lending relationship, which also positively impacts the access to credit for borrowers (Boot, 2000). Relationship banks also provide liquidity in deteriorating financial situations of individual firms (Elsas and Krahnen, 1998).

As one of the dominating causes for changes in liquidity patterns we detect a bad client's base as the observed liquidity shift could be linked to bad borrowers being forced to draw down their existing credit lines. If we assess this result against the background of different financial intermediation systems, we expect that this finding is not limited to the marketed-oriented banking scheme, but should also hold for the balance-oriented one: Unused commitments being drawn by clients experiencing refinancing problems is not a specific feature of the US banking industry, but also holds for European banks (see also Elsas and Krahnen, 1998).

Besides a bad client base we also find empirical proof that window dressing in combination with money market financing is one of the main explanations for the documented liquidity shift. If we now link this finding with the observed structural differences between Continental Europe and the US, we acknowledge that money markets are far more important for US banks and that relationship banking should

[43] Since Bankscope data is available for both Continental European and US banks, we use this database in order to guarantee comparability between the two regions. We tried to match Bankscope data for Continental Europe with the US FDIC database applied in this paper, but retrieved misleading results due to different definitions of individual balance sheet positions.

have a stronger impact on the composition of the asset side in the case of European banks as their flexibility to manage the asset side in particular with regard to loans is limited. In other words, based on window dressing activities, we expect the shift in liquidity positions to be more accentuated in a market-oriented than in a balance sheet-oriented banking system.

Turning our attention towards existing literature on this matter, we find in Bechmann and Raaballe (2010) an interesting example opposing to our results: The authors show that in the case of Denmark – as an example for a balance sheet-oriented financial intermediation system – the banking sector in total followed a policy of high term transformation before the recent financial crisis in which several banks had to be bailed out by the Danish government. Yet, we have to consider that during the years prior to the financial crisis the Danish banking system carried country-specific characteristics (e.g. deposit deficit against loans of 20%, extreme growth of long-term lending activities fueled by short-term deposits of foreign banks). With the intensifying financial crisis the deposits of foreign banks were not prolonged and Danish banks experienced refinancing difficulties and, accordingly, suffered from their high levels of term transformation. Assuming that this increase in term transformation particularly also holds for failed banks, we would expect that a bad client base leads to a shift in liquidity patterns. However, the Danish banking crisis was mainly driven by liquidity pressure on the liability side. Thus, the potential effect of our second identified cause (window dressing) should be more accentuated. An increase in short-term (foreign) deposit funding in the case of Danish banks should also lead to an adjustment of the asset side (e.g. less loans and more short-term assets). In such an environment we would expect that changes in liquidity patterns might occur as documented for failed banks in the US. Yet, Bechmann and Raaballe (2010) observe that even though the Danish banking system experienced a massive inflow of short-term capital, it did not adjust on average (including failed and non-failed banks) its asset-side as lending activities were increased. We attribute this finding to the dominance of relationship banking in Denmark.

6.6. Conclusion

In this paper we analyze the liquidity dynamics of bank defaults. Our approach employs a data sample that covers all FDIC-ruled banks and financial institutions within the US banking industry over a period of nine and a half years and, most importantly, 329 bank defaults. Using this data, we observe that failing and surviving banks manage their liquidity positions differently and detect the following main patterns:

First, defaulting banks drift away from the traditional business model of banks by abandoning a (positive) term transformation, culminating about three years before default. This shift is driven by an increase in liquidity-relevant assets (e.g. short-term loans). Second, we document that this liquidity shift is induced by window dressing activities towards bondholders and money market investors as well as a bad client base. Third, not income diversification drives the insolvency risk of banks, but endogenous changes in the capital structure. We show that liquidity-relevant asset and liability positions have a significant impact on default patterns.

Appendix 6-I: Mean and Median of Liquidity-Relevant Assets and Liabilities to Total Balance Sheet

This table presents the median and mean values of the liquidity-relevant asset and liabilities positions relative to the balance sheet total. The sample covers balance sheet information reported to the FDIC for the period 2001 to H1-2010 on a quarterly basis. Values are reported for failed (F) and non-failed (NF) banks separately. For the failed banks, t = 0 corresponds to the last available data before default. Non-failed banks are ordered to reflect the default pattern of failing banks and hence control for any industry-wide developments. Significance levels for

Share of Balance Sheet Total

	Median						Mean						Significance of Difference between Non-Failed and Failed Samples	
	Liquidity-Relevant Assets			Liquidity-Relevant Liabilities			Liquidity-Relevant Assets			Liquidity-Relevant Liabilities				
	NF	F	NF-F	NF	F	NF-F	NF	F	NF-F	NF	F	NF-F	Assets	Liabilities
t = -19	44.0%	45.5%	-1.4%	53.7%	49.1%	4.6%	43.7%	44.0%	-0.3%	53.0%	48.1%	4.9%		***
t = -18	44.5%	46.1%	-1.7%	54.8%	46.7%	8.1%	44.2%	44.8%	-0.5%	53.8%	47.4%	6.4%		***
t = -17	44.1%	49.5%	-5.4%	54.0%	48.4%	5.6%	43.8%	46.1%	-2.2%	53.0%	47.6%	5.4%	*	***
t = -16	42.8%	51.2%	-8.4%	53.2%	46.4%	6.8%	42.9%	47.5%	-4.6%	52.5%	46.2%	6.2%	***	***
t = -15	42.7%	52.3%	-9.6%	52.2%	46.8%	5.4%	42.8%	47.3%	-4.6%	51.4%	45.8%	5.6%	***	***
t = -14	43.7%	52.5%	-8.9%	53.5%	45.9%	7.5%	43.5%	48.1%	-4.6%	52.5%	45.5%	7.0%	***	***
t = -13	43.4%	53.4%	-10.0%	53.5%	46.8%	6.7%	43.2%	48.1%	-4.9%	52.4%	45.9%	6.6%	***	***
t = -12	41.9%	54.0%	-12.2%	53.3%	45.1%	8.2%	42.0%	48.4%	-6.4%	52.2%	44.8%	7.4%	***	***
t = -11	41.5%	52.0%	-10.4%	52.4%	44.8%	7.6%	41.7%	47.8%	-6.1%	51.4%	44.3%	7.1%	***	***
t = -10	41.8%	51.3%	-9.5%	53.5%	44.5%	9.0%	41.7%	46.8%	-5.1%	52.1%	44.7%	7.5%	***	***
t = -9	40.1%	48.2%	-8.1%	53.0%	43.9%	9.0%	40.5%	45.6%	-5.1%	51.7%	44.2%	7.5%	***	***
t = -8	37.6%	47.3%	-9.7%	53.7%	43.5%	10.3%	38.3%	44.3%	-6.0%	52.4%	43.7%	8.7%	***	***
t = -7	36.4%	44.5%	-8.0%	52.5%	43.9%	8.7%	37.4%	43.0%	-5.6%	51.3%	43.2%	8.1%	***	***
t = -6	35.1%	41.4%	-6.2%	52.8%	43.1%	9.8%	36.3%	41.2%	-4.9%	51.6%	43.3%	8.3%	***	***
t = -5	35.1%	38.7%	-3.6%	52.2%	41.2%	11.0%	36.3%	38.7%	-2.5%	51.1%	42.8%	8.3%	**	***
t = -4	33.7%	36.1%	-2.4%	53.0%	40.8%	12.2%	35.3%	37.0%	-1.8%	51.9%	42.3%	9.7%	*	***
t = -3	33.5%	35.8%	-2.3%	53.3%	40.2%	13.2%	35.0%	35.8%	-0.8%	52.3%	41.2%	11.0%		***
t = -2	33.7%	33.3%	0.4%	54.8%	39.8%	15.0%	35.4%	34.8%	0.5%	53.4%	41.4%	12.0%		***
t = -1	34.4%	32.9%	1.5%	54.2%	39.3%	14.9%	35.8%	33.8%	2.0%	53.0%	40.8%	12.2%	**	***
t = 0	33.8%	31.9%	1.8%	54.6%	40.2%	14.4%	35.1%	33.0%	2.1%	53.4%	41.4%	12.0%	**	***

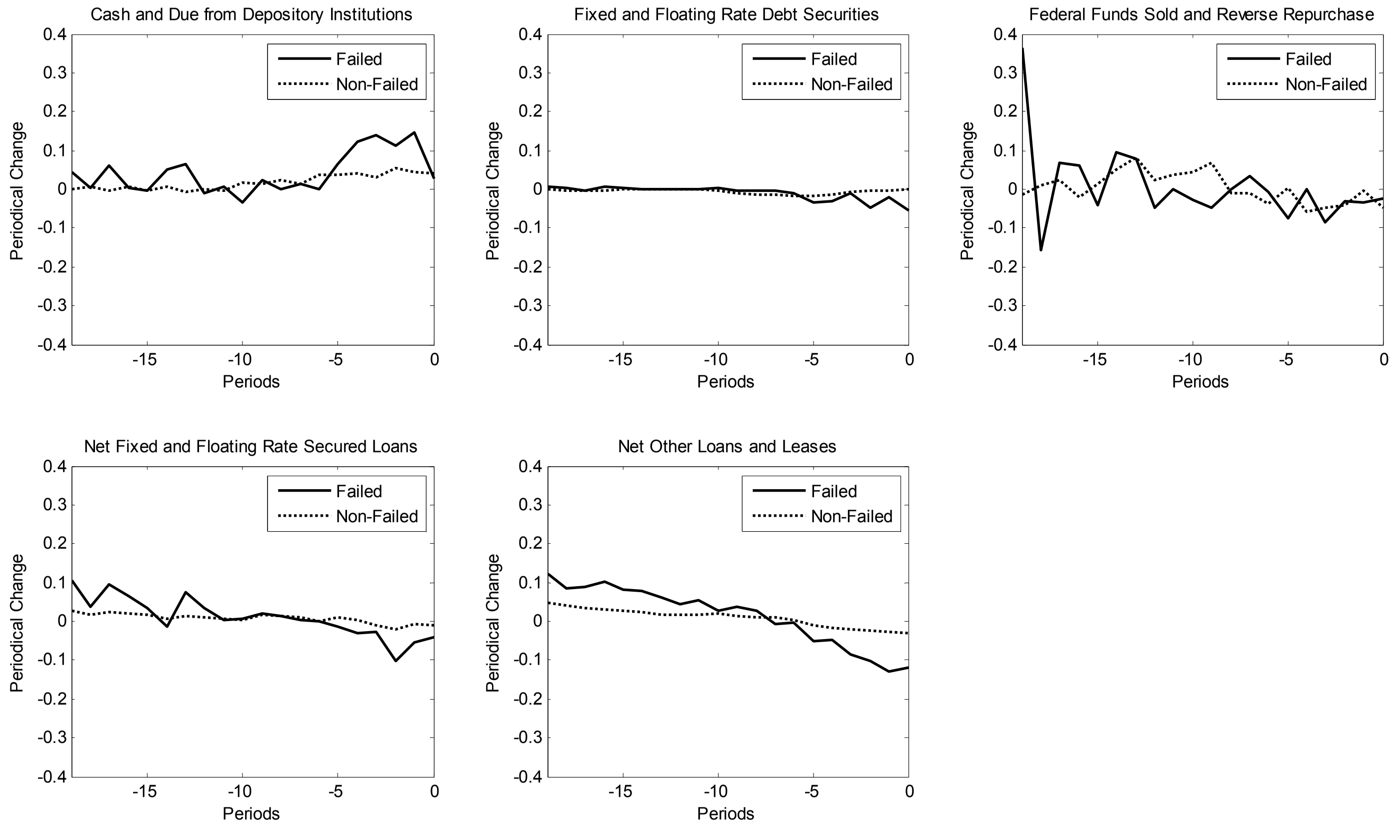
** indicates significant group differences on the 10%-level.*

*** indicates significant group differences on the 5%-level.*

**** indicates significant group differences on the1%-level.*

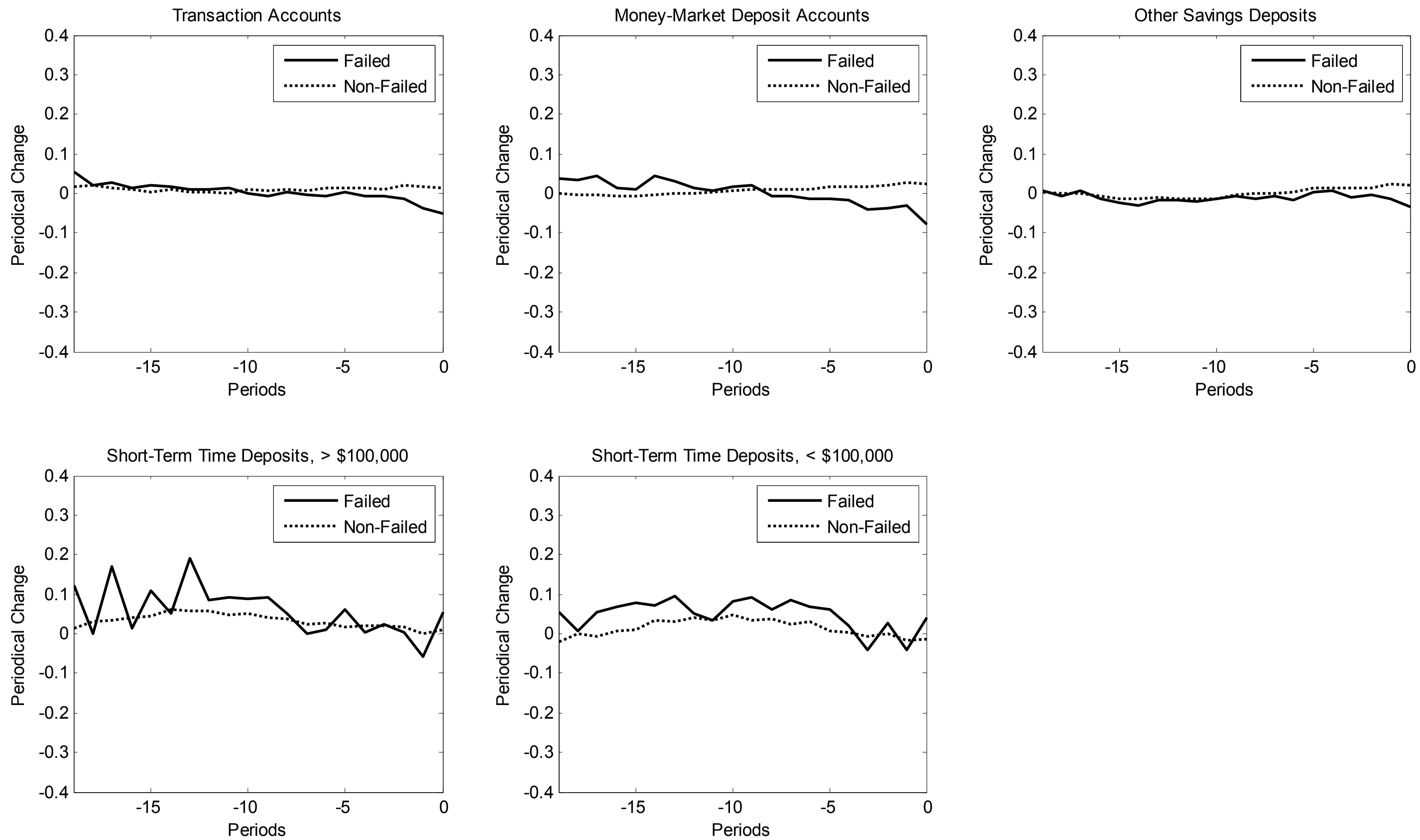
Appendix 6-II: Median Growth of Liquidity-Relevant Balance Sheet Items, Asset-Side

This figure presents the median growth of the most important liquidity-relevant balance sheet positions of the asset-side. Values are reported for the sample of failed banks and the sample of non-failed banks separately. For the failed banks, period 0 corresponds to the last available data before default. Non-failed banks are ordered to reflect the default pattern of failing banks.



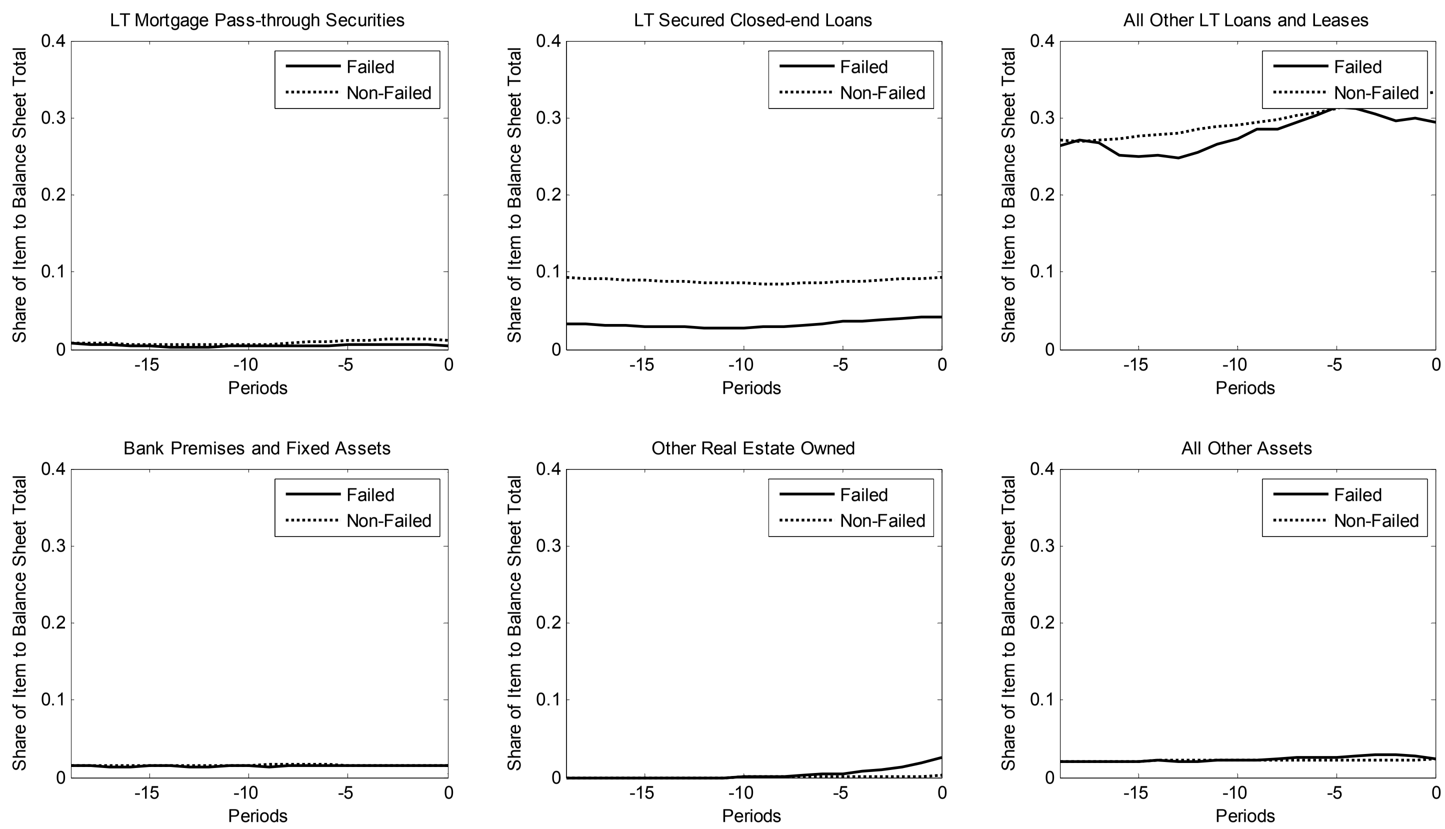
Appendix 6-III: Median Growth of Liquidity-Relevant Balance Sheet Items, Liability-Side

This figure presents the median growth of the most important liquidity-relevant balance sheet positions of the liability-side. Values are reported for the sample of failed banks and the sample of non-failed banks separately. For the failed banks, period 0 corresponds to the last available data before default. Non-failed banks are ordered to reflect the default pattern of failing banks.



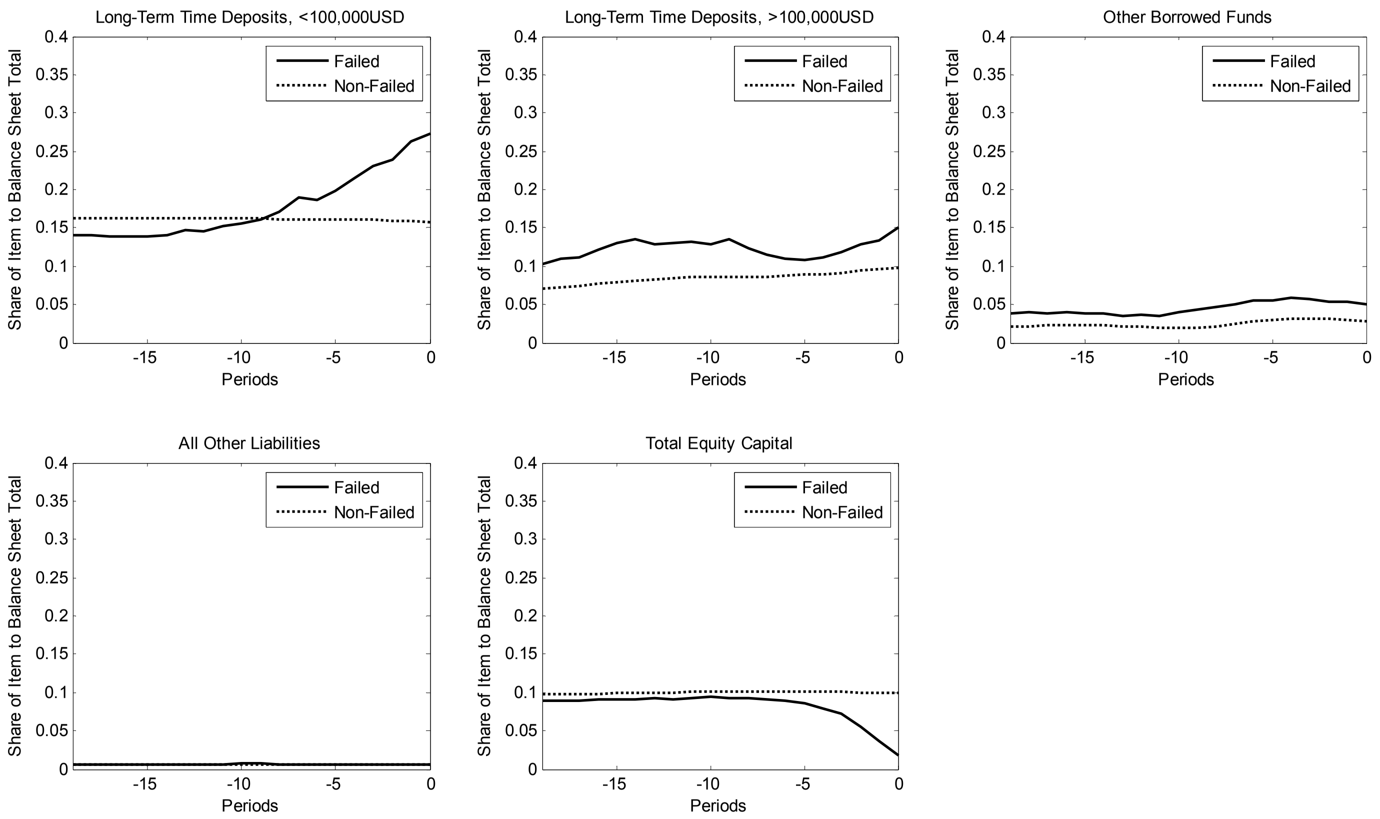
Appendix 6-IV: Median of Illiquid Balance Sheet Items to Balance Sheet Total, Asset-Side

This figure presents the median evolution of the illiquid balance sheet positions on the asset-side for failed banks and non-failed bank separately. For the failed banks, period 0 corresponds to the last available data before default. Non-failed banks are ordered to reflect the default pattern of failing banks. Any illiquid asset positions with a median of zero in all periods are not included in the figure. All values are calculated in relation to the balance sheet total.



Appendix 6-V: Median of Illiquid Balance Sheet Items to Balance Sheet Total, Liability-Side

This figure presents the median evolution of the illiquid balance sheet positions on the liabilities-side for failed banks and non-failed bank separately. For the failed banks, period 0 corresponds to the last available data before default. Non-failed banks are ordered to reflect the default pattern of failing banks. Any illiquid liability positions with a median of zero in all periods are not included in the figure. All values are calculated in relation to the balance sheet total.



References

Allen, F. and Gale, D., ‘Competition and financial stability’, *Journal of Money, Credit, and Banking* **36**, 2004, 433–480.

Altunbas, Y., Carbo, S., Gardener, and Molyneaux, E., ‘Examining the relationship between capital, risk and efficiency in European banking’, *European Financial Management* **13**, 2007, 49-70.

Arena, M., ‘Bank failures and bank fundamentals: A comparative analysis of Latin America and East Asia during the nineties using bank-level data’, *Journal of Banking & Finance* **32**, 2008, 299-310.

Bank, M. and Lawrenz, J., ‘Deposit finance as a commitment device and the optimal debt structure of commercial banks’, *European Financial Management*, forthcoming.

Bechmann, K., Raaballe, J., ‘Bad corporate governance and powerful CEO´s in banks: poor performance, excessive risk-taking, and a misuse of incentive-based compensation’, *Working Paper*, February 2010.

Boot, A., ‘Relationship banking: What do we know? ’, *Journal of Financial Intermediation* **9**, 7-25.

Boyd, J. and De Nicolo, G., ‘The theory of bank risk-taking and competition revisited’, *Journal of Finance* **60**, 2005, 1329–1343.

Campello, M., Giambona, E., Graham, J. and Harvey, C., ‘Liquidity Management and Corporate Investment During a Financial Crisis’, Working Paper, July 14, 2010.

Cole, R. and Gunther, J., ‘Separating the likelihood and timing of bank failure’, *Journal of Banking and Finance* 19, 1995, 1073-1089.

Cole, R. and Gunther, J., ‘Predicting bank failures: A comparison of on- and off-site monitoring systems’, *Journal of Financial Services Research* **13(2)**, 1998, 103-117.

Demirgüç-Kunt, A. and Huizinga, H., ‘Bank activity and funding strategies: The impact on risk and returns’, *Journal of Financial Economics* 98 (3), 2010, 626-650.

Diamond, D. and Rajan, R., ‘A theory of bank capital’, *Journal of Finance* **LV**, 2000, 2431-2465.

Elsas, R. and Krahnen, J., ‘Is relationship lending special? Evidence from credit-file data in Germany’, *Journal of Banking and Finance* **22**, 1998, 1283-1316.

Fries, S., Mella-Barral, P. and Perraudin, W., ‘Optimal bank reorganization and the fair pricing of deposit guarantees’, *Journal of Banking and Finance* **21**, 1997, 441–468.

Goddard, J., Liu, H. and Molyneux, P., 'Do banks profit converge?', *European Financial Management*, forthcoming.

King, T. and Wen, M., 'Shareholder governance, bondholder governance, and managerial risk-taking', *Journal of Banking and Finance* **35**, 2011, 512–531.

Leland, H., 'Agency costs, risk management, and capital structure', *Journal of Finance* **LIII**, 1998, 1213–1243.

Lepetit, L., Nys, E., Rous, P. and Tarazi, A., 'Bank income structure and risk: An empirical analysis of European banks', *Journal of Banking and Finance* **32**, 2008, 1452–1467.

Niinimaki, J., 'Evergreening in banking', *Journal of Financial Stability* 3, December 2007, 368-393.

Ongena, S. and Smith, D., 'The duration of bank relationships', *Journal of Financial Economics* **61**, 2011, 449-475.

Pontell, H., 'Control fraud, gambling for resurrection, and moral hazard: Accounting for white-collar crime in the savings and loan crisis', *Journal of Socio-Economics* **34**, December 2005, 756-770.

Wheelock, D. and Wilson, P., 'Why do banks disappear? The determinants of US bank failures and acquisitions', *Review of Economics and Statistics* **81**, 2000, 127-138.

7. An Alternative Way of Calculating Risk-based Deposit Insurance Premiums

Susanna Walter*, Matthias Schaller**

New Paradigms in Banking, Financial Markets and Regulation, SUERF Study 2012/2

Abstract

The pricing of deposit insurance premiums traditionally uses expected loss approaches for the calculation of premium charges. Merton (1977) opened up a second branch using option pricing methods for the evaluation of the risk a bank poses to the deposit insurance scheme. We present an innovative methodology to allocate deposit insurance premiums among financial institutions that uses elements of both approaches: We use standard key figures on capitalization and liquidity from expected loss models on deposit insurance pricing and integrate these figures into a stochastic process based on the Merton framework. Hence, we are able to build on the advantages of a multi-indicator model while still using the dynamic information of option pricing models. Our empirical validation of the model suggests that our pricing algorithm is in fact able to discriminate between the riskiness of banks and it is also highly sensitive to worsening conditions of a financial institution.

Keywords: *Deposit Insurance, Risk-based premium, Covered Deposits, Expected loss, Option Pricing, Basel 3*

JEL Classification: G1, G18, G21, G22, G28, G30, G32, G33.

---

* University of St. Gallen (e-mail: susanna.walter@unisg.ch), ** University of St. Gallen (matthias.schaller@unisg.ch)

7.1. Introduction

The recent financial crisis once again proved that the financial industry is decisively different from other industries. One of the major differences is that the collapse of a competitor does not strengthen the position of everybody else in the market but can rather lead to a domino effect that ultimately drags down the whole financial system and, undoubtedly then, the economy. Even though most governments were ultimately forced to take steps in mitigating the turmoil, the financial safety nets of most countries proved to be quite effective in protecting the financial institutions. This is especially true for deposit insurance as one of the core elements of a financial safety net. While the financial system as a whole was very fragile during the crisis, the deposit insurance schemes at least managed to prevent bank-runs throughout most of the crisis.

Deposit Insurance schemes (in short: DIS), however, are no free lunch. Traditional moral hazard theory argues that deposit insurance creates a strong incentive for the management of banks to choose exceptionally high leverage and for the customers of banks to loosen their monitoring activities. As with other types of insurance, moral hazard is most important when the premium of deposit insurance does not properly reflect the effective underlying risk associated with the activities of the banks. Accordingly, moral hazard could be partially mitigated by introducing risk-adjusted premiums to deposit insurance schemes. This, however, proofs to be a very challenging subject as it is all but clear, what the actual bank risk is and how it should be measured.

Current academic as well as practical literature shows that there is still no fair and pragmatic calculation method according to the broad requirements for the calculation of risk-based premiums in deposit insurance as specified by JRC (2009). However, the need for such a system is going to be explicitly anchored in the revision draft of the Directive 94/19/EC and the complementary Directive 2009/14/EC (see JRC 2010b). As a typical feature of a self-regulatory framework, the original Directives (as well as relating recommendations and principles such as FSF 2001 and IADI 2009) and the revision endeavours stipulate that the costs of funding deposit insurance systems should be borne by the appropriate members (i.e. the credit institutions). However, the regulations give no details on how such risk-based premiums should be determined in order to augment an ex-ante deposit insurance fund (DIF).

The aim of our paper is therefore to contribute to this discourse by introducing a Merton-based, risk-adjusted calculation of deposit insurance premiums. Our approach combines the advantages of expected loss pricing and option pricing theory in an innovative framework. It relies on established key figures from expected loss pricing for the assessment of a bank's riskiness, but at the same time, incorporates the time-variant information included in option-pricing theory.

The remainder of this article is organized as follows: The next section provides an overview of the relevant previous research in the area of the risk-based pricing of deposit insurance premiums. The third section elaborates on our theoretical modelling framework. In the fourth and fifth section, we test our model based on data of the US banking sector for the years 2002 to 2009. The final section discusses and concludes the paper.

7.2. Literature Review

There is a strong consensus in research as well as in practice that risk-based premiums for deposit insurance schemes are - mainly in combination with ex-ante funding – preferable to flat premium pricing. The reason is that risk-adjusted premiums for deposit insurance are most capable of preventing moral hazardous behaviour since it penalizes riskier banks (Keeley 1990, Marshall and Prescott 2001, Bartholdy et al. 2003, Demirguç-Kunt and Huizinga 2004, Demirguç-Kunt et al. 2007). Additionally, as Pennacchi (2005) shows, risk-based deposit insurance premiums generate smaller pro-cyclical effects than risk-based capital requirements. Thus, the pro-cyclical impact of Basel II can be reduced by strengthening risk-based deposit insurance premiums.

There are two relevant streams for the calculation of deposit insurance, expected loss pricing and Merton-type approaches. Expected loss pricing, originally stemming from credit risk management, is centred on a bank's expected probability of default (PD). This PD can be estimated using fundamental data (i.e. capitalization ratios) or market data (i.e. credit spreads). Since market data is not available for the large part of most banking sectors, risk-adjusted deposit insurance premiums that are currently in place rely on expected loss pricing based on fundamental data. A comprehensive overview on the risk-based methods that are currently adopted in five countries in the EU27 (Germany, France, Portugal, Italy, Finland and Sweden) as well as on the method currently in place in the US are summarized in JRC (2008). The major drawback of expected loss pricing is its strong focus on point-in-time assessment of PDs. Hence, expected loss pricing mostly disregards any dynamic behaviour in the development of relevant key figures.

Merton-type approaches for the calculation of deposit insurance premiums are able to remedy this shortfall of expected loss pricing. These approaches employ elements of option pricing theory based on Black and Scholes (1973). The original Merton framework (1977) uses these principles in order to estimate the probability of default of companies in a time-continuous setting. The default process of a company is driven by the value of assets and the value of liabilities. The resulting default probability is therefore explicitly linked not only to current values of the firm's assets, but also to its variability. One major drawback of Merton's (1977) original framework is that it uses the asset value and volatility of a bank's assets in order to derive its riskiness. Both parameter are unobservable and therefore prevent the model from practical adoption. Marcus and Shaked (1984) and Ronn and Verma (1986) were the first to address this issue using the observable market value of equity and its volatility of listed banks. Additionally, there are several papers proposing methods on how to estimate the effective and market-based equity value as well as its volatility (Kuester and O'Brien 1991, Barth et al. 1992, Cooperstein et al. 1995, Duffie et al. 2003, Falkenheim and Pennacchi 2003, Eom et al. 2004).

We contribute to both streams of literature on risk-adjusted deposit insurance premiums: Regarding the Merton approach, our model circumvents to problem of estimating equity values by using data that is readily available for most banks in all developed countries. We then use key figures derived from expected loss pricing for the estimation of probabilities of default of banks and incorporate these figures into the time-continuous setting of the Merton-type approaches.

7.3. Methodology

As a necessary requirement of our approach, we assume that the total fund payments per period are exogenously pre-specified. This is in line with most approaches currently in use (EBF 2010, JRC 2010) and also most likely to pass political decision processes. This reflects a DIS where the target rate of total fund size to total insured deposits is pre-defined as well as the period during which this target rate should be reached (accumulation period). This assumption of an exogenously determined fund size considerably facilitates the calculation of premium payments since it reduces the question of the riskiness of the banks to a question of the relative riskiness of a bank compared to the other banks in the sector. Additionally, any systemic risk components in the banking industry might be neglected under the assumption that the systemic risk is homogenously distributed across the financial institutions. Assuming exogenously fixed total premium payments and abstracting from systemic risk components, the only remaining relevant factors for the calculation of deposit insurance premiums are a contribution base and a factor reflecting the risk profile of a bank (JRC 2008, JRC 2009, Bernet and Walter 2009).

Our model uses several steps for the calculation of a bank's contribution to the overall fund inflows of a certain period: In the first step, it is necessary to identify the set of p relevant variables *X* that are useful for predicting the stability of bank i. Depending on the focus of the setup for the DIS, the variables could either be derived from credit rating analysis, research on bank stability, or key figures of regulatory schemes. It is worthwhile noting that the set of variables could consist of any number of variables. In the second step, these variables are included in a logistic regression as independent variables, whereas bank default is the dependent variable. The resulting propensity score of bank i for period t is calculated using the following equation:

$$PS_{i,t} = \frac{exp\left(\beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \ldots + \beta_p \cdot X_p\right)}{1 + exp\left(\beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \ldots + \beta_p \cdot X_p\right)}$$

PS: Propensity Score

i: Bank

t: Period

β: Coefficient

X: Independent Variable

p: Number of Covariates

The usage of logistic regression does, of course, restrict the model to banking systems with a sufficient number of bank failures in order to calibrate the model. However, if this requirement is met, the calculation of propensity scores automatically includes statistically optimized weightings to each of the variables based on the coefficient estimated by the logistic regression. The calculated propensity score $PS_{i,t}$ reflects a value that corresponds to the riskiness of bank i in period t, based on the historical information of failed versus non-failed banks in the respective banking sector. In order to come up with a time series of propensity scores, this procedure has to be repeated for each bank and each period. The resulting time series of propensity scores constitutes a vector of a single variable that incorporates the relevant and available information on each particular bank.

Now, taking the stochastic process of bank i,

$$PS_i = [PS_{i,1} \quad \dots \quad PS_{i,T}],$$

PS: Propensity Score

i: Bank

t: Period

it is possible to calculate the corresponding mean μ_i and standard deviation σ_i of the propensity scores. Assuming log-normally distributed values of propensity scores allows specifying the bank-specific stochastic process associated with the propensity scores as:

$$dPS_{i,t} = \mu_i dt + \sigma_i dW_t$$

PS: Propensity Score

i: Bank

t: Period

W: Standard Wiener Process

μ: Mean

σ: Standard Deviation

Staying with the Merton terminology, the time-constant value of liabilities is set to unity. Since the range of values of the propensity scores and the survival propensity is [0; 1] this means that the put option associated with the stochastic process is always at- or in-the-money. From an economic perspective, this might be interpreted as the immanent risk of default, that even the safest financial institutions pose to the banking system. Following Merton (1977), the fair value of the put option associated with the process can be written as:

$$P(PS_{i,T}) = \theta(h_2) - \frac{1}{(PS_{i,T} + 1)} \cdot \theta(h_1)$$

where

$$h_1 = \frac{\left\{log(PS_{i,T} + 1) - \frac{{\sigma_i}^2 \cdot T}{2}\right\}}{\sigma_i \sqrt{T}},$$

$$h_2 = h_1 + \sigma_i \sqrt{T}.$$

P: Put Option Value

PS: Propensity Score

T: Observation Period

σ: Standard Deviation

Whereas the Merton model uses the deposit-to-asset value ratio, our model uses the propensity score of the banks increased by one. The constant addition of one is necessary as the average propensity scores are very low, i.e. closer to zero than to one. The original Merton framework works with deposit-to-asset values in the range close to one and accordingly, the model has the best discriminatory power in this area. By adding one to the propensity scores, we are able to make better use of the discriminatory power, while the basic concept of the pricing algorithm remains unchanged.

The put value calculated for each bank reflects its risk component. In the next step, this risk component is multiplied with the bank-specific contribution base. In the case of deposit insurance, the contribution base are the covered deposits $CD_{i,t}$ of the bank which reflect the effective exposure to a DIF. In order to come up with the final contribution of each financial institution, these risk components - weighted by the contribution base - need to be transformed into values relative to the overall payment. The relative risk contribution, multiplied with the total payments per period, constitute the deposit insurance premium per bank in the respective period $DIP_{i,T}$:

$$DIP_{i,T} = \frac{P_{i,T} \cdot CD_{i,T}}{\sum_{i=1}^{I} P_{i,T} \cdot CD_{i,T}} \cdot PP_t$$

DIP: Deposit Insurance Premium

P: Put Option Value

ID: Covered Deposits

PP: Total Premium Payments

i: Bank

t: Period

This model requires a set of assumptions: Regarding assumptions related to technical and structural aspects of premiums, we incorporate no regulatory forbearance or other bailout assistance options (such as M&A). Furthermore, we assume compulsory membership of banks as recommended by most academic literature (Garcia 1999, Demirguç-Kunt et al. 2003) as well as (self-) regulatory framework components and underlying principles (Directive 94/19/EC 1994, JRC 2010, and IADI 2009). This compulsory membership prevents adverse selection problems otherwise associated to deposit insurance schemes. We further assume that all banks actually pay their risk-based premiums (e.g. the government has the power to oblige banks which accept domestic covered deposits to pay for their risk-based premiums). Finally, we abstract from any auditing or fund-related overhead costs and abstract from interest income of financial investments of accumulated fund assets.

In the following section, we want to present one potential alteration to the pricing model that uses an Ornstein-Uhlenbeck process as underlying stochastic process:

$$dPS_{i,t} = \omega(\mu_i - PS_{i,t})dt + \sigma_i dW_t$$

PS: Propensity Score

i: Bank

t: Period

W: Standard Wiener Process

μ: Mean

σ: Standard Deviation

ω: Mean-Reversion Factor

This process is able to capture mean-reverting behaviour in the propensity scores of the banks. The, now time-variant drift of the process is calculated as the difference of the long-run average of propensity scores and the current propensity score, scaled by a mean-reversion factor between zero (no mean-reversion) and one (complete mean-reversion). If a significant part of the predictor variables in the logistic regression exhibit a mean-reverting behaviour, this characteristic should also be incorporated to the process for propensity scores.

To illustrate the adequacy of mean-reversion, we assume a model that includes the capitalization of banks as predictor of bank riskiness. The basic Gaussian stochastic process is designed to meet the development of stock prices. Abstracting from a constant drift, the best estimator of the next value is the current value. This, however, might not be reasonable for capitalization levels of banks. To a great extent, the general level of the capitalization of a bank is a strategic decision of the bank's management that trades-off aspects of profitability and bank stability. Only subsequent to regime changes in the regulatory or competitive environment, which we do not incorporate in our model, capitalization ratios should evolve to new stationary levels. Accordingly, the best estimator for a capitalization might not be the current value, but a value somewhere between the current value and the target capitalization of the bank. This results in a mean-reverting process, described by the Ornstein-Uhlenbeck characterization.

7.4. Data Sample

In this section, we test our model using data of the US banking sector. We require information on the contribution base of each bank (i.e. the size component), the risk factors used to derive the propensity scores and assumptions regarding the total premium payments per period.

As contribution base, we choose the covered deposits of each bank. Covered deposits include all deposits of banks that use deposit insurance. As the exposure of the DIF is restricted to these deposits, covered deposits effectively mirror the maximum exposure a bank imposes on the DIF. In the case of the USA, covered deposits are protected or insured deposits repayable by the guarantee scheme under the appropriate national law. In the USA, all traditional types of bank accounts - checking, savings, trust, certificates of deposit (CDs), money market deposit accounts and IRA retirement accounts – are insured by the Federal Deposit Insurance Corporation (FDIC) if the respective financial institution is a member of the FDIC. The insurance is limited to an amount of $250,000 per customer.

It is important to note that the empirical analysis is only one illustration of the potential applications of the calculation methodology. There is a wide variety of factors that might be included in the determination of bank risk. The actual choice of variables might also be influenced by several external factors, e.g. political, academic, or the availability of data. In this example, we focus on variables derived from the Basel III framework. Two major pillars of the current Basel framework are capitalization and liquidity. Accordingly, we incorporate one variable on each of these two dimensions of bank stability. With regard to capitalization, we choose tier 1 ratios as indicator. This variable is - designed as minimum requirement - also the variable that is included into the Basel framework. In accordance with current regulatory efforts to strengthen liquidity requirements of banks, we also include the liquidity cushion of banks into our analysis. Basel III proposes two different key figures on liquidity: The liquidity coverage ratio and the net stable funding ratio. The data required for the calculation of any of the two figures, however, is not yet available. Hence, we restrain our analysis to the cash ratio. The cash ratio indicates to what extent an institution is able to meet its short-term obligations using its most liquid assets. In the beginning of the empirical analysis, we will provide evidence on the separation power of both variables with regard to bank default.

Concerning the total premium payments per year, there are two relevant factors: the designated reserve ratio and the accumulation period. The reserve ratio (or relative fund size) of a deposit insurer is the ratio of fund reserves to total covered deposits. In general, it needs to be “adequate to at least cover the potential losses of the insurer under normal circumstances” (IADI 2009). The Dodd-Frank Act establishes a maximum designated reserve ratio for the USA of 1.5 % of estimated covered deposits (FDIC 2011). As a comparison, in the EU27, the practically adopted target ratio relative to covered deposits is at a median of 1.75 %, excluding Romania as an outlier with a target coverage of 10 % (Hoelscher et al. 2006). In accordance to the US and European specifications we fix our relevant coverage ratio at 1.5 % of covered deposits.

Regarding the accumulation period of the target fund size, recommendations range from 5 to 17 years (JRC 2008, EBF 2010, FDIC 2011). For our analysis, we choose a time frame of 10 years or a respective 40 quarters. This period reflects a hypothetical example of a newly established ex-ante financed deposit insurance fund in the US banking sector. For our calculations, we need to detect the quarterly amount of premium inflows that reaches the target size of 1.5% of the CD within the period of 10 years. To keep the calculations simple, we abstract from any compounding effects in real terms. This results in quarterly target premium payments of 0.0375% of covered deposits across all banks, assuming a stable economic environment with a negligible amount of bank failures.

Our empirical analysis is based on quarterly balance sheet as well as income statement data of all US-American banks and thrift institutions registered with and reported to the Federal Deposit Insurance Corporation (FDIC) for the time period 01/01/2001 – 6/30/2010. For financial years before 2001 the FDIC does not report quarterly figures. Therefore, our data sample is limited to a total of 38 periods. Over the investigated time period, a total of 10,966 different financial institutions reported to the FDIC on a quarterly basis (see Table 7-1). 329 of these institutions either failed in the course of the sample period or needed an assistance transaction to be able to continue business. In the following, this subsample is referred to as failed banks (F).

The second subsample amounts to 10,637 non-failed banks (NF), which reported at least once in the course of the observation period to the FDIC and neither defaulted nor required any assistance transactions. For each year we display the number of reports available for the respective subsample (e.g. in 2001 there were 270 reports available of banks that eventually defaulted in the subsequent years). In order to avoid a selection bias we also include all quarterly reports submitted by banks that were acquired by a competitor in the course of the observation period. Comparability and correctness of the data points reported by the banks is ensured by the standardized FDIC data collection process. This holds in particular for the classification of individual positions. Accordingly, the definition of our tier 1 capital matches with the FDIC and includes common equity plus noncumulative perpetual preferred stock plus minority interests in consolidated subsidiaries less goodwill and other ineligible intangible assets. The amount of eligible intangibles, including mortgage servicing rights in core capital is limited in accordance with supervisory capital regulations. By limiting the data sample to FDIC-registered banks we ensure that all banks are obliged to a comparable regulation framework.

Table 7-1: Summary Statistics on FDIC Data on Bank Statistics

Year	Reports Available NF	*Reports Available F*	*Bank Defaults*	Employees (Median) NF	*Employees (Median) F*	Employees (Mean) NF	*Employees (Mean) F*	Balance Sheet Total* (Median) NF	*Balance Sheet Total* (Median) F*	Balance Sheet Total* (Mean) NF	*Balance Sheet Total* (Mean) F*
2001	9,343	*270*	*9*	32	*41*	173	*1,306*	92.5	*122.4*	679.3	*5,654.1*
2002	9,086	*269*	*6*	33	*46*	181	*1,400*	99.1	*147.6*	744.0	*6,247.1*
2003	8,906	*276*	*5*	34	*49*	187	*1,392*	105.2	*171.1*	809.7	*6,768.8*
2004	8,693	*284*	*1*	34	*55*	193	*1,500*	110.6	*214.4*	904.1	*7,927.1*
2005	8,539	*296*	-	35	*61*	196	*1,651*	117.2	*251.0*	957.6	*9,152.9*
2006	8,378	*305*	*1*	36	*65*	199	*1,782*	122.8	*304.1*	1,017.4	*10,995.0*
2007	8,234	*305*	*4*	36	*70*	203	*1,802*	128.8	*337.0*	1,122.3	*12,486.9*
2008	8,035	*274*	*57*	37	*61*	210	*1,682*	138.0	*316.1*	1,288.8	*12,676.1*
2009	7,883	*137*	*160*	37	*50*	210	*2,747*	149.1	*296.1*	1,280.4	*20,273.5*
H1 - 2010	7,847	*32*	*86*	37	*57*	207	*4,439*	151.8	*331.1*	1,300.0	*33,161.7*
Total	**10,637**	***329***	***329***	**35**	***55***	**195**	***1,746***	**119.0**	***227.4***	**998.0**	***10,655.7***

** in million USD*

In the first year, the sample of non-failing institutions contains 9,343 reports. This number continuously decreases to 7,847 reports filed at the end of 06/2010. The decrease of filed reports is a result of industry consolidation through mergers and acquisitions. The pattern behind the number of reports available for failed institutions is determined by the recent financial crisis. Throughout the period before the current crisis, the number of reports filed every year slightly increased from 270 in 2001 to 305 in the period just before the financial crisis started in 2007. With an increasing number of banks defaulting from the beginning of 2007, this figure starts to decrease until the end of mid-2010 (32). In the last two years, the failed sample decreases dramatically as the majority of the failures happened within these two years. Generally, the failed sample contains larger institutions in terms of workforce and balance sheet total than the sample of non-failing institutions. The median of failing banks employs 55 full time equivalents (FTE) whereas the median of non-failing banks employs only 35 FTEs. The respective mean values are by far larger, which is due to the largest banks in both samples that skew mean values to higher levels. Similar relations are also reflected in the balance sheet total as a second proxy for bank size.

In the next section, we want to elaborate on the applicability of the data for our pricing methodology. We proceed in three steps: In the first section, we show the separation power of tier 1 ratios and cash ratios with regard to bank default. In the second section, we test the lognormal distribution of the respective underlying time series. In the third section, we test for mean-reverting behaviour as one of the potential extensions to our model.

In Figure 7-1 and Figure 7-2, we plot the development of median tier 1 ratios as well as the cash ratios of banks that eventually defaulted against their surviving peers. For the failing sample, the right hand side of the graph is fixed as the respective default value. Q38 reflects the value directly prior to default and the precedent quarters are assembled so that period 37 reflects the value one period before default and so on. The surviving peers are ordered to meet the default pattern of the failing sample, meaning that the relative impact in period 38 is governed by the distribution of failures over time. Using this approach, we control for any industry dynamics or changes in regulatory regimes that might affect systematic changes in the tier 1 and liquidty levels. There are three interesting findings in these developments: First, for the tier 1 ratios, the non-failing banks show relatively stable values throughout the whole observation period. This suggests that changes in industry dynamics, if so, only play a minor role in the changes of tier 1 ratios. Second, the tier 1 ratios of the failing sample are distinctively lower over the whole observation period than for their surviving peers. Third, tier 1 ratios drop in the direct advent of default resulting in a median value directly before default of only 2.2%.

For the liquidity ratio the picture is somewhat different: First, there is some variance in the control groups, which suggests that, especially during the recent financial crisis, there were distinctive alterations in the liquidity cushion in the whole banking industry. Second, we find that failing banks have on average a lower liquidity cushion throughout most of the observation period. Third, in the direct advent of default, which corresponds to the period of the financial crisis for most of the bank failures, there is clear evidence for liquidity hording. To account for this effect, we exclude the last year before default in our analysis on the discriminatory power of the liquditiy ratio.

Figure 7-1: Development of Tier 1 Ratios towards Default.

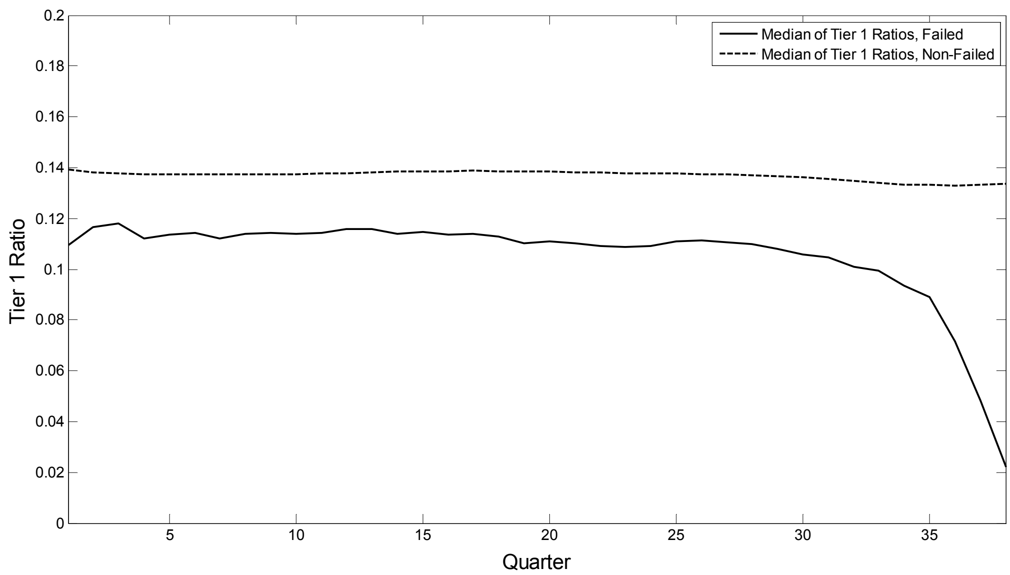
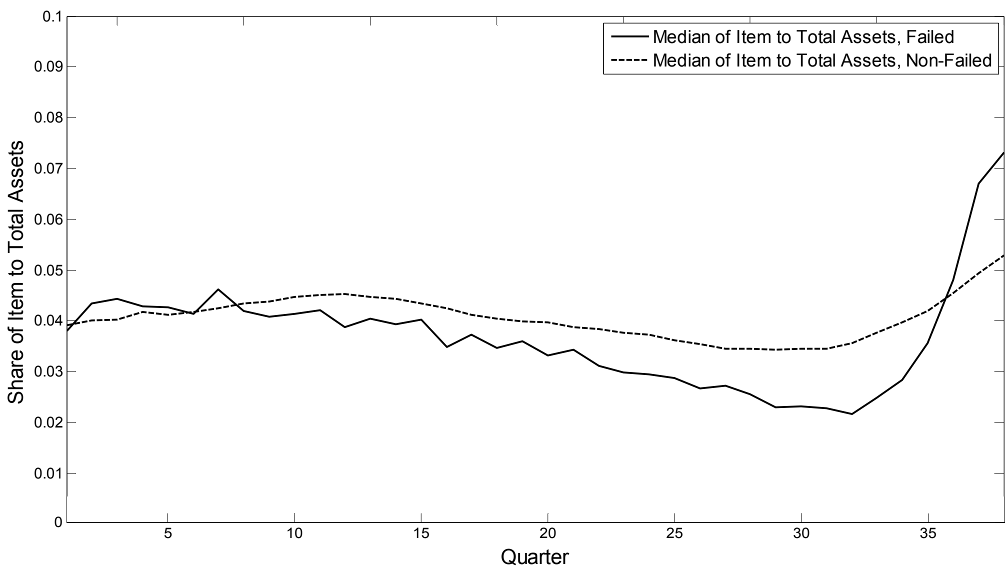


Figure 7-2: Development of Liquidity Ratios towards Default.



We deepen this analysis by looking at the density distribution of both, the tier 1 ratio and the liquidity ratio. Figure 7-3 and Figure 7-4 show the results for the two subgroups of failing and non-failing banks. The results match with the findings of the previous analysis and show that both variables appear to have high discriminatory power with regard to bank default. Most importantly, this does not only account for the direct advent of default but also for the medium- to long-term.

In order to apply most of the approaches based on Black and Scholes, a log-normal distribution of the underlying values is required. We examine the log-normal distribution of propensity scores using the Lilliefors specification test (Lilliefors 1967). It uses the null hypothesis that the sample stems from a distribution in the normal family. Our approach requires a separate simulation for every financial institution. Hence, log-normal distribution is a necessary requirement for the data on every bank that is included in the simulation.

Figure 7-3: Tier 1 Ratios at Default vs. Control Group

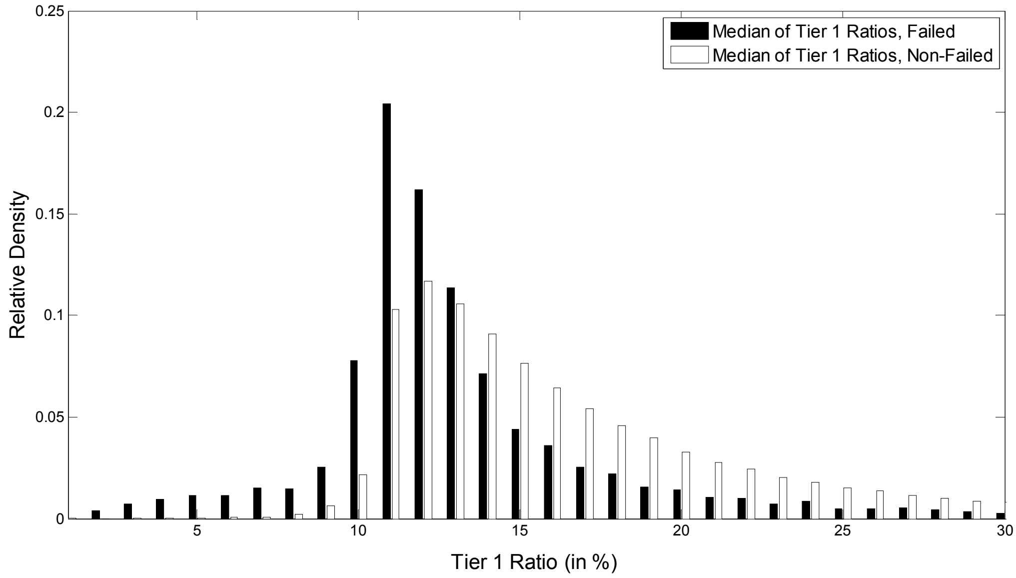
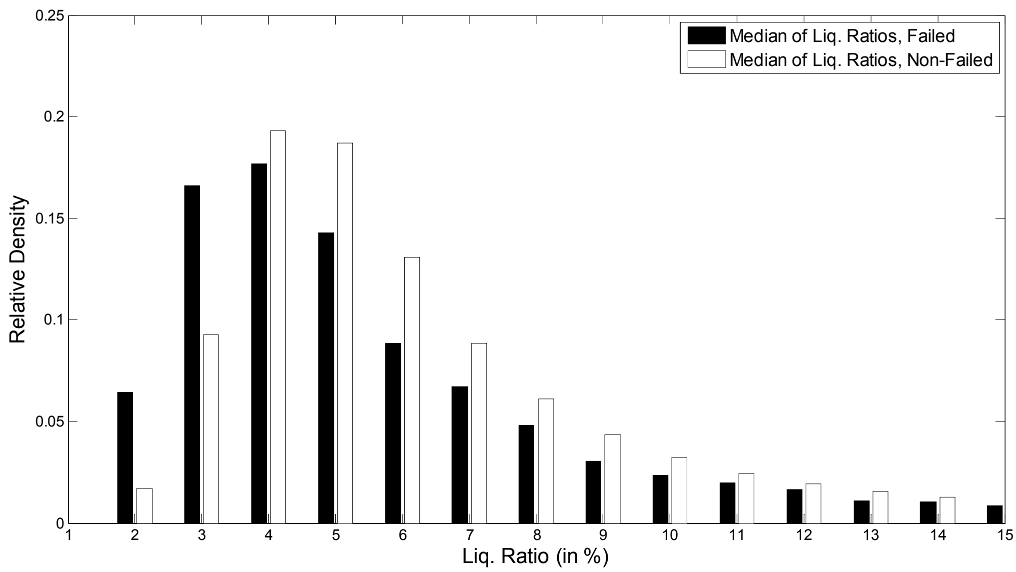
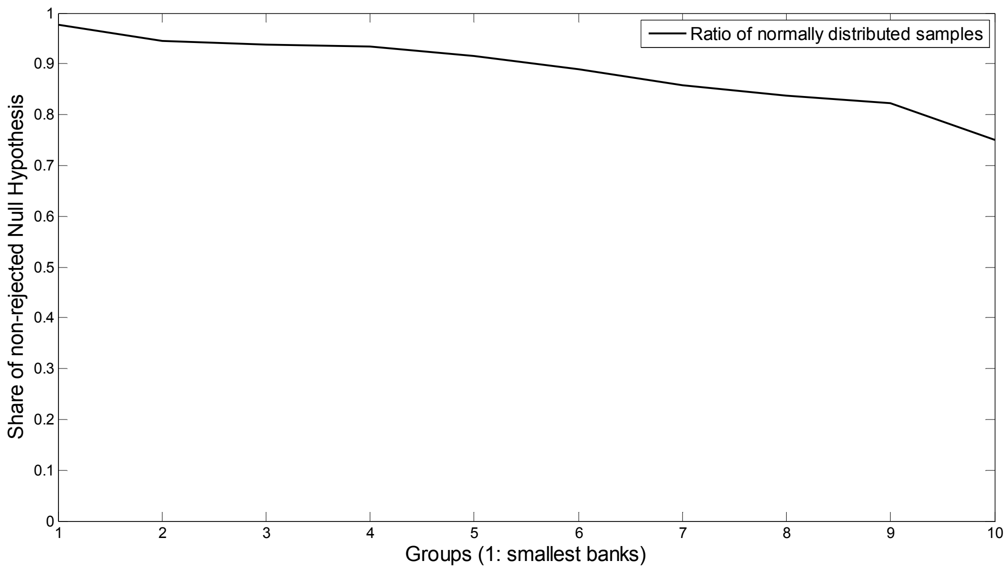


Figure 7-4: Liquidity Ratios at Default vs. Control Group



Using a significance level of 1 %, we find that overall 70.1 % of the samples do not require rejecting the null hypothesis of log-normally distributed values. Even though this value suggests that there is indeed a significant share of financial institutions whose propensity scores do not exhibit a log-normal distribution, there is a large degree of heterogeneity in the results. When we control for outlier and size effects, the results look quite different: An exclusion of changes in propensity scores larger than +/-30% increases the share of non-rejected null hypotheses to a value of 88.6 %. If we control for differences in the size of banks by dividing the sample into ten cohorts of increasing balance sheet size, the corresponding results are depicted in Figure 7-5. The share of non-rejected null hypotheses and, therefore, supposedly log-normally distributed values increases with a decrease in balance sheet size. For the sample with the smallest banks, this ratio reaches 97.7 %. For the largest sample, the value does not exceed 75.1 %.

Figure 7-5: Share of log-normally Distributed Propensity Scores over Size



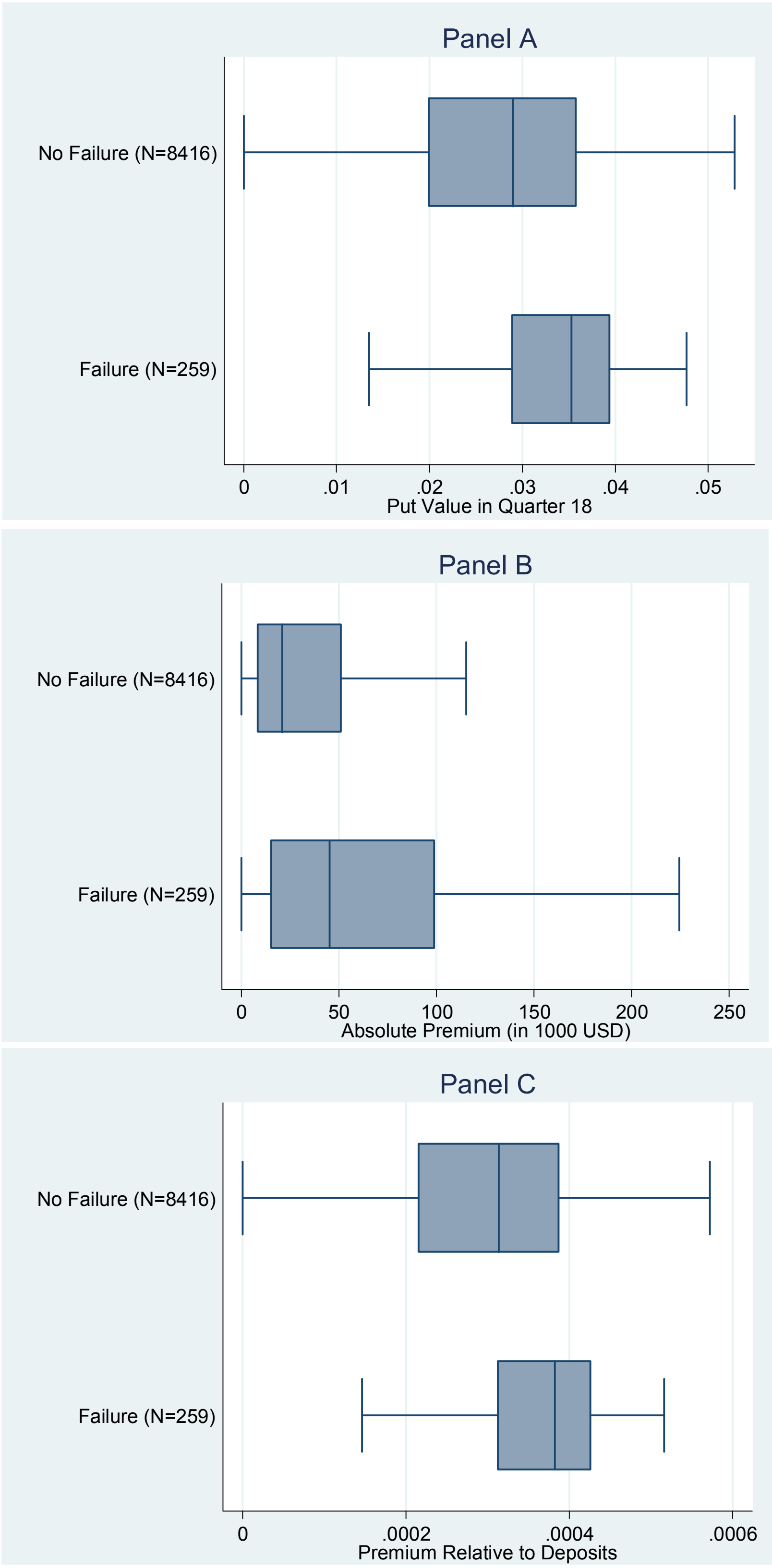
As with most applications of the option pricing approaches, the tests of the log-normal properties of the underlying data deliver mixed results. The model assumptions are most accurately met for smaller banks and hence the pricing results are most accurate for this subsample. Our analysis suggests that most rejections of the lognormal distribution stem from the disproportionate share of outlier values. Overall, we are not able to reject or confirm the assumption of log-normally distributed propensity scores. However, since the findings rather suggest not rejecting the null hypothesis of lognormal distribution, we proceed with the full data sample for the empirical analysis.

7.5. Empirical Validation

We test our model using the data sample as described in the previous section. Additionally, the input parameters reflect the results of our analyses. We assume log-normal distribution of propensity scores within banks. Following our description of the pricing methodology for risk-adjusted deposit insurance premiums, we calculate the value of the bank-specific put option for each bank separately, based on the propensity score and a time horizon of one year. This horizon corresponds to a scenario with quarterly premium payments. We assume total target premium payments of 0.0375% of covered deposits per quarter in order to reach the target fund size of 1.5% within a period of ten years.

To test our methodology, we split our data sample in two periods, one for the quarters 1-18 and one for the quarters 19-38. The first period is used to calculate the hypothetical premium payments in a calm market environment. We then use these payments and the information on which banks defaulted during the second period to compare the premium payments of failing banks with their surviving peers. If our pricing methodology is in fact able to identify banks with a riskier business model, we should find that premium payments are distinctively higher for the failed sample. Figure 7-6, Panel A to C show the resulting distribution of premium payments across banks. Panel A shows the distribution of the put values as calculated with our pricing methodology. The values range from 0.0000195 to 0.0639, with a mean of 0.0270 and a standard deviation of 0.0106. For the failing banks, the average is distinctively higher at a value of 0.0326. Keeping in mind that these hypothetical premium payments are calculated for a scenario where the failing banks are 5 years prior to their actual default date, it appears that tier 1 ratio and cash ratio do well in discriminating risky from save banks even in the medium- to long run.

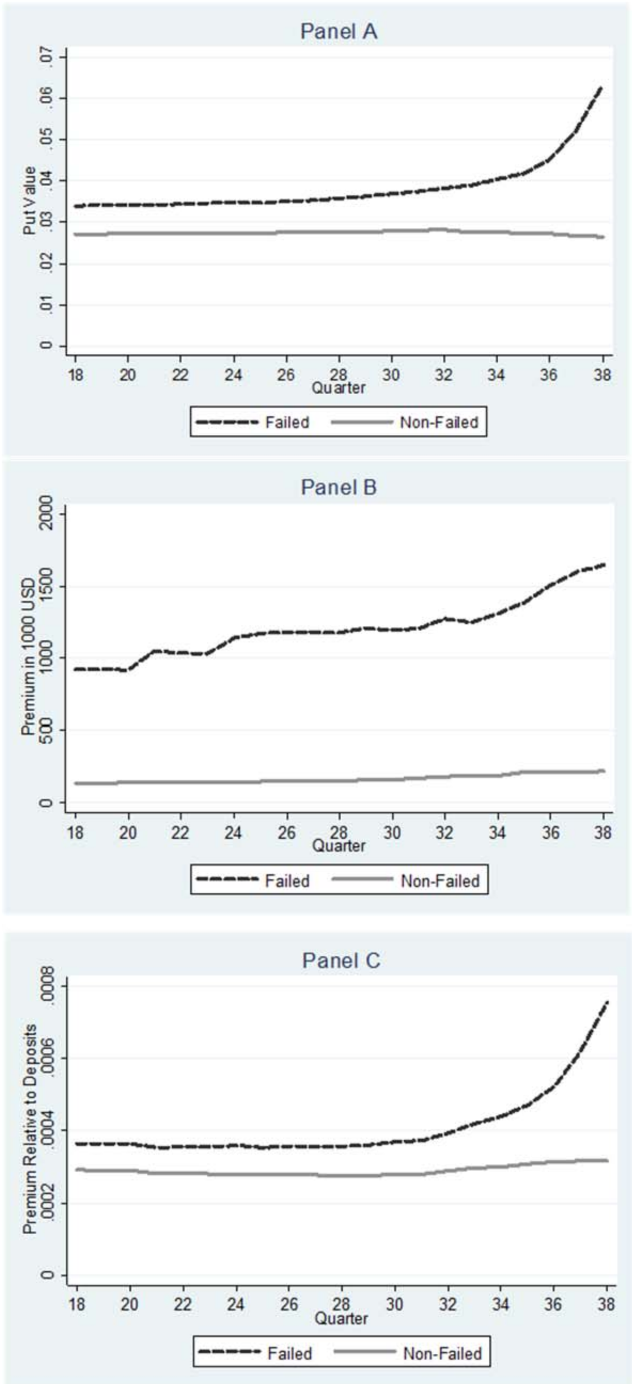
Figure 7-6: Resulting Values at the End of Quarter 18



Panel B shows the actual premium payments in USD for one year based on our pricing algorithm. According to the findings of Panel A, the least risky banks in the non-failing sample are only charged marginal premium payments of 509 USD. The maximum premium payment for the bank with the largest single risk amounts to 79.8 million USD, while the mean is 135,000 USD. Taking the relatively long accumulation period into account, the average premium payments are necessarily quite modest. The larger differences between the failing sample and the non-failing sample as compared to the put values reflect the above-average amount of deposits in the failing sample. Here, the mean premium payment amounts to 938,800 USD with a minimum of 59,000 USD and a maximum of 163 million USD. Panel C shows the differences in the premium payments per bank in relation to the respective insured deposits. By design, the dollar-weighted average of payments is 0.375% of insured deposits. The actual premium payments, however, range from virtually zero to 0.692% of insured deposits. While failing banks pay an (unweighted) average of 0.353% of insured deposits, their surviving peers only pay 0.293% of insured deposits.

In the next step, we test whether our model is also able to capture the worsening strength of banks on their immediate path towards default. Following our previous analyses on the discriminatory power of tier 1 ratios and cash ratios, we expect to find that, using a rolling window for the premium calculation, deposit insurance premiums should significantly increase for the banks that approach a default situation as opposed to the banks that did not default. Figure 7-7 Panel A to C show the results of this calculation using a rolling window of 18 quarters. All findings confirm the results from the previous analysis with a distinctive difference between failing and non-failing sample in quarter 18. Additionally, Panel A and Panel C show that the discrepancy between failing and non-failing banks dramatically increases when approaching the default date. Most importantly, the put values and premium payments of the non-failing sample remain at relatively constant levels throughout the whole simulation period while the payments for the failing sample sharply increase. With regard to premium payments relative to insured deposits, Panel C shows that the increase in premium charges is economically significant for the failing sample. Five years prior to default, the average premium payment amounts to 0.365%. In the quarter directly prior to the default, this value more than doubles to an average of 0.755%. When looking at the absolute premium payments in Panel B, it is interesting to see that all payments increase modestly over time, which suggests an increase in total deposits. However, this increase is more pronounced for the failing sample and adds to the increasing premium charges for this group.

Figure 7-7: Development of Prediction Values toward Default



In the final step, we want to test whether using a mean reverting process instead of the ordinary stochastic process in the calculation is reasonable based on the properties of our data. In the theoretical description of our methodology, we argue that mean reversion might be applicable for the evolution of tier 1 ratios and cash ratios. Additionally, we find that for both, tier 1 ratios and cash ratios, the values of most banks appear to cluster around pre-set target ranges. These ranges are influenced by a trade-off of higher costs associated with higher levels of capitalization and liquidity and higher risk of default associated with lower levels. Accordingly, it might be necessary to incorporate mean-reverting behavior also into the resulting propensity scores. Assuming a linear relationship between the propensity score and the mean reversion factor, it is possible to conduct an OLS-regression to estimate the magnitude of the mean-reverting effect. The dependent variable is the percentage deviation of the propensity score from its bank-specific long-run average; the independent variable is the percentage change in the propensity score in the subsequent quarter. The coefficient resulting from the regression is then equal to the mean-reversion factor in the Ornstein-Uhlenbeck process. The results of the regressions are summarized in Table 7-2:

Table 7-2: Results of OLS-Regression of PD-factors for Mean Reversion.

Dependent: Change in Propensity Score During Next Period

Independent	**Coefficient**	**Std. Error**	**t**	**P > |t|**
Deviation from Propensity Score Mean	-0.0216***	0.00442	-4.88	0.000
Constant	*0.110****	*0.0109*	10.09	0.000
Method	OLS			
R-squared	0.001			
Observations	318,284			

The results suggest a statistically significant correlation between the change in propensity scores and its current deviation from the mean value. According to the coefficient, the mean reversion of propensity scores amounts to -2.2%, which means that, abstracting from any constant drift, the expected value of a tier 1 ratio in period t

+ 1 is 2.2% closer to its mean level than the ratio in t = 0. This value is statistically significant at the 1%-level. The negative sign of the coefficient is also in line with expectations meaning that the deviation from the mean value is expected to be decreased in the next step. These results suggest that there is in fact mean-reverting behaviour in the propensity scores of banks. However, the magnitude of this effect with 2.2% is very small and the effect would be constant across all banks in our calculation. In unreported robustness checks, we test the actual impact on our previous results. We find only marginal deviations from the base case without mean-reversion. Taking this finding into account, we conclude that, even though there is evidence for mean-reverting behaviour in the actual data, the effect seems to be too small to justify the additional complexity associated with the solution of the Ornstein-Uhlenbeck process.

7.6. Discussion

In the light of the recent financial crisis, the European directives on deposit insurance premiums, 94/19/EC as well as 2009/14/EC, are going to be revised, while the U.S.A already adopted several improvements (FDIC 2011). Accordingly, the design of risk-adjusted deposit insurance premiums is a hot topic in the academic and the political discourse. While the theoretical concept of the approaches based on Merton are highly sophisticated, they are hardly feasible since the data required is simply not available. On the contrary, traditional expected loss models build on a point-in-time evaluation of bank stability and lack the ability to incorporate any time-variant dynamics. Since our approach combines elements of a multiple indicator model and option pricing theory, it is able to capture advantages of both approaches. The advantage of the option pricing approach is that it uses both, information on the actual value of assets as well as its historic values for the estimation of bank riskiness. A bank is hence ceteris paribus more prone to default when it a) has a lower current asset value and b) historically higher changes in the asset values. This dynamic perspective comes at the cost that only one process is taken into account (e.g. the asset value). On the other hand, a simple multiple indicator model for the prediction of bank default offers the possibility to include several predictor variables, such as in our example one figure on capitalization and one on liquidity. It suffers, however, from the shortcoming that it only takes the current state into account and hence neglects any information on the variability of the variables. Our approach, in contrast, uses the dynamic perspective of option pricing models but is still able to aggregate several variables into the underlying process.

Our empirical analysis with data from the US banking sector shows that our pricing methodology is able to discriminate between risky and safe banks by charging higher rates to the failing banks. We additionally find that worsening conditions of a banking institution are also reflected in the premium. An introduction of mean-reversion in the underlying stochastic process might be reasonable in this context. However, we find that the data support mean-reversion only to a marginal extent. Our model might certainly be improved by extending the input variables for the logistic regression to a more sophisticated identification model of bank riskiness. Hence, we want to stress that our application with only two predictor variables is only an introduction to the potential applications of the pricing methodology. The liquidity figures introduced in Basel III are certainly a very promising alternative to our current liquidity figure, once the data is available over a reasonable horizon.

References

Barth, J. R., Page, D. E. & Brumbaugh, D. (1992). Pitfalls in Using Market Prices to Assess the Financial Condition of Depository Institutions. *Journal of Real Estate Finance and Economics,* 5(2), pp. 151-166.

Bartholdy, J., G.W. Boyle & Stover, R.D. (2003). Deposit Insurance and the Risk Premium in Bank Deposit Rates. Journal of Banking and Finance, 27(4), pp. 699-717.

Bernet, B. & Walter, S. (2009). Design, Structure and Implementation of a Modern Deposit Insurance Scheme. Vienna: SUERF.

Black, F. & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy, 81, pp. 637-654.*

Cooperstein, R., Pennacchi, G. G. & Redburn, S. F. (1995). The Aggregate Cost of Deposit Insurance: A Multiperiod Analysis. *Journal of Financial Intermediation, 4, pp. 242-271.*

Demirguç-Kunt, A. & Huizinga, H. (2004). Market Discipline and Deposit Insurance. *Journal of Monetary Economics, 51*, pp. 375-399.

Demirguç-Kunt, A., Kane, E. J. & Leaven, L. (2003). Adoption and Design of Deposit Insurance. In A. Demirguç-Kunt, E. Kane & L. Leaven (2008)*, Deposit Insurance Around the World: Issues of Design and Implementation.* Cambridge: MIT press.

Demirguç-Kunt, A., Kane, E. J. & Laeven, L. A. (2007). Determinants of Deposit-Insurance Adoption and Design. *Journal of Financial Intermediation, 17(3)*, pp. 407-438.

Duffie, D., Jarrow, R., Purnanandam, A. & Yang, W. (2003). Market Pricing of Deposit Insurance. *Journal of Financial Services Research, 24(2-3)*, pp. 93-119.

EBF (2010). Positioning in respect of the European Commission's proposal for a recast Directive on Deposit Guarantee Schemes – EBF final position. Unpublished document.

Eom, Y., Helwage, J. & Huang, J. Z. (2004). Structural Models of Corporate Pricing: An Emopirical Analysis. *Review of Financial Studies, 17, No. 2*, pp. 499-544.

Falkenheim, M. & Pennacchi, G. (2003). The cost of deposit insurance for privately held banks: A market comparable approach. *Journal of Financial Services Research, 24*, pp. 121–148.

FDIC, Federal Deposit Insurance Corporation (2011). Designated Reserve Ratio.

FSF, Financial Stability Forum (2001). Guidance for Developing Effective Deposit Insurance Systems. Working Group on Deposit Insurance. Report. Found on http://www.fdic.gov/deposit/deposits/international/guidance/guidance/finalreport.pdf

Garcia, G. (1999). Deposit Insurance: A Survey of Actual and Best Practices. IMF. Internatinoal Monetary Fund. Working Paper, No. 99/54.

Hoelscher, D. S., Taylor, M. & Klueh, U. H. (2006). The Design and Implementation of Deposit Insurance Systems. IMF. Occasional Paper.

IADI, International Association of Deposit Insurers (2009). Funding of Deposit Insurance Systems. Bank for international settlements. Found on http://www.iadi.org/docs/Funding%20Final%20Guidance%20Paper%206_May_2009.pdf

JRC, Joint Research Centre (2008). Risk-Based Contributions in EU Deposit Guarantee Schemes: Current Practices. Found on http://ec.europa.eu/internal_market/ bank/guarantee/index_en.htm

JRC, Joint Research Centre (2009). Possible Models for Risk-Based Contributions to DGS, http://ec.europa.eu/internal_market/bank/guarantee/index_en.htm

JRC, Joint Research Centre (2010). Deposit Guarantee Schemes. Impact Assessment. Found on http://ec.europa.eu/internal_market/bank/guarantee/index_en.htm

Keeley, M. C. (1990). Deposit Insurance, Risk, and Market Power in Banking. *The American Economic Review, 80*(5), pp. 1183-1200.

Kuester, K. A. & O'Brien, J. (1991). Market-Based Deposit Insurance Premiums: An Evaluation. Board of Governors of the Federal Reserve System. Finance and Economics Discussion Series, No. 150.

Lilliefors, J. (1967). On the Kolmogorov-Smirnov Test for Normality with Mean and Variance Unknown. *Journal of the American Statistical Association, 62*, pp. 399-402.

Marcus, A. J. & Shaked, I. (1984). The Valuation of FDIC Deposit Insurance Using Option-pricing Estimates. *Journal of Money, Credit, and Banking, 16*, pp. 446-460.

Marshall, D. A. & Prescott, E. S. (2001). Bank capital regulation with and without state-contingent penalties. *Carnegie-Rochester Conference Series on Public Policy, 54(1)*, pp. 139-184.

Merton, R. (1977). An Analytic Derivation of the Cost of Deposit Insurance and Loan Guarantees. *Journal of Banking & Finance, 1,* pp. 3-11.

Ornstein, L.S., Uhlenbeck G. E (1930).: On the theory of Brownian Motion. *Physical Review*. 36, pp. 823–841.

Pennacchi, G. (2005). Risk-based capital standards, deposit insurance, and procyclicality. *Journal of Financial Intermediation, 14*, pp. 432-465.

Ronn, E. & Verma, A. (1986). Pricing Risk-Adjusted Deposit Insurance: An Option-Based Model. *Journal of Finance, 11*, pp. 871-895.

8. *Where is my Dent?*

In the first ten years of the 21st century, two of the supposedly most developed economic regions have experienced financial crises that not only brought their financial sectors to the brink of collapse, but also governments and the economies as a whole. The subprime crisis in the USA and the sovereign-debt crisis in the European Union are two lively examples that research on financial stability is still a hot topic.

The different research projects presented throughout this dissertation deal with three different aspects that affect the stability of the financial sector from three different angles: Efficient loan portfolios that help banks generate stable profits, the banks' appropriate liquidity cushions that are needed in case a bank incurs losses nonetheless, and finally risk-adjusted deposit insurance in case the banks not just tremble but actually fall. The first study on the efficient design of loan application processes sheds doubt on the dominating view that loan officers use their discretion to incorporate soft information in the rating process. We find that loan officers use their discretionary power to insure clients against fluctuations in their credit conditions. Yet, what we also find is that it is probably not even the intent to insure clients that drives the loan officers' behaviour. Rather they simply try avoiding renegotiations about with their clients interest rates.

The second study on efficient loan processes shows that the loan officers' intrinsic motivation is crowded-out by strategic considerations if a loan officer is controlled by a second person. In particular, it appears that loan officers do not assign more efficient ratings under control, but rather try to anticipate and counteract potential corrections. In line with this interpretation, we find that more experienced loan officers show a stronger bias under control, just as loan officers that have frequently been corrected in previous applications do.

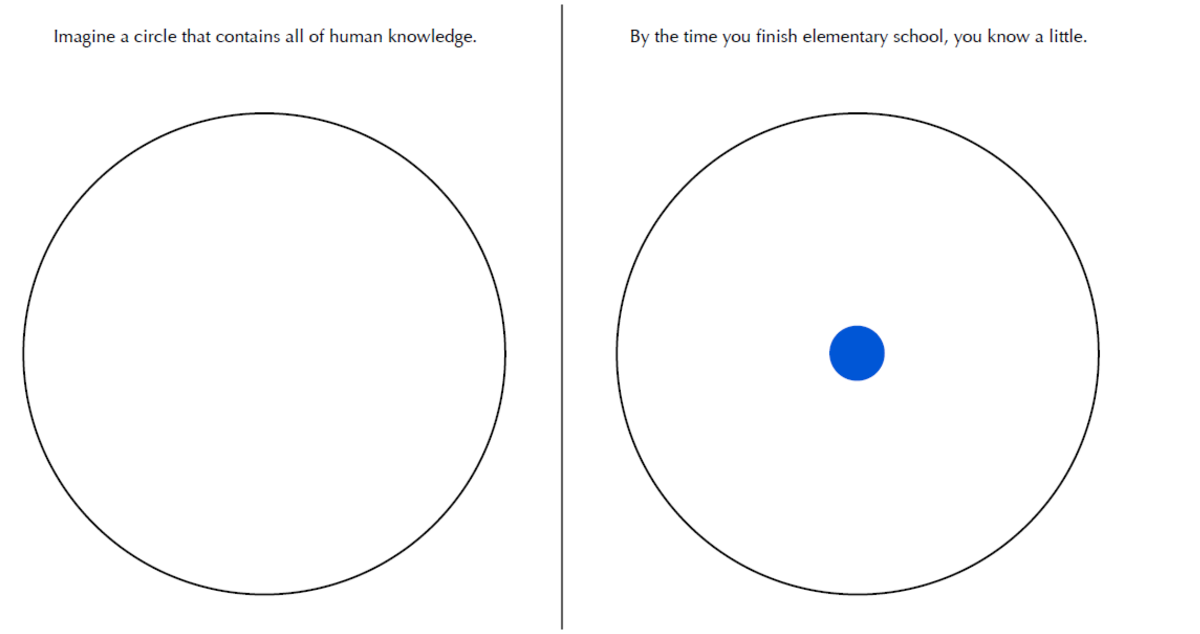
The third study on the banks' liquidity position prior to default yields very interesting findings in the light of the current regulatory effort to implement minimal liquidity ratios: While the lack of liquidity certainly fuelled the fragility of financial institutions during the subprime crisis, the results indicate that high levels of costly liquidity are detrimental to bank stability in the medium- to long-run and might hence rather serve as a valuable predictor of future bank distress. In the advent of default, in an attempt to window-dress for institutionalized debt investors, thus trying to prevent silent bank-runs, banks increase their liquidity holdings, which decreases the term transforming activities and thus reduces interest income.

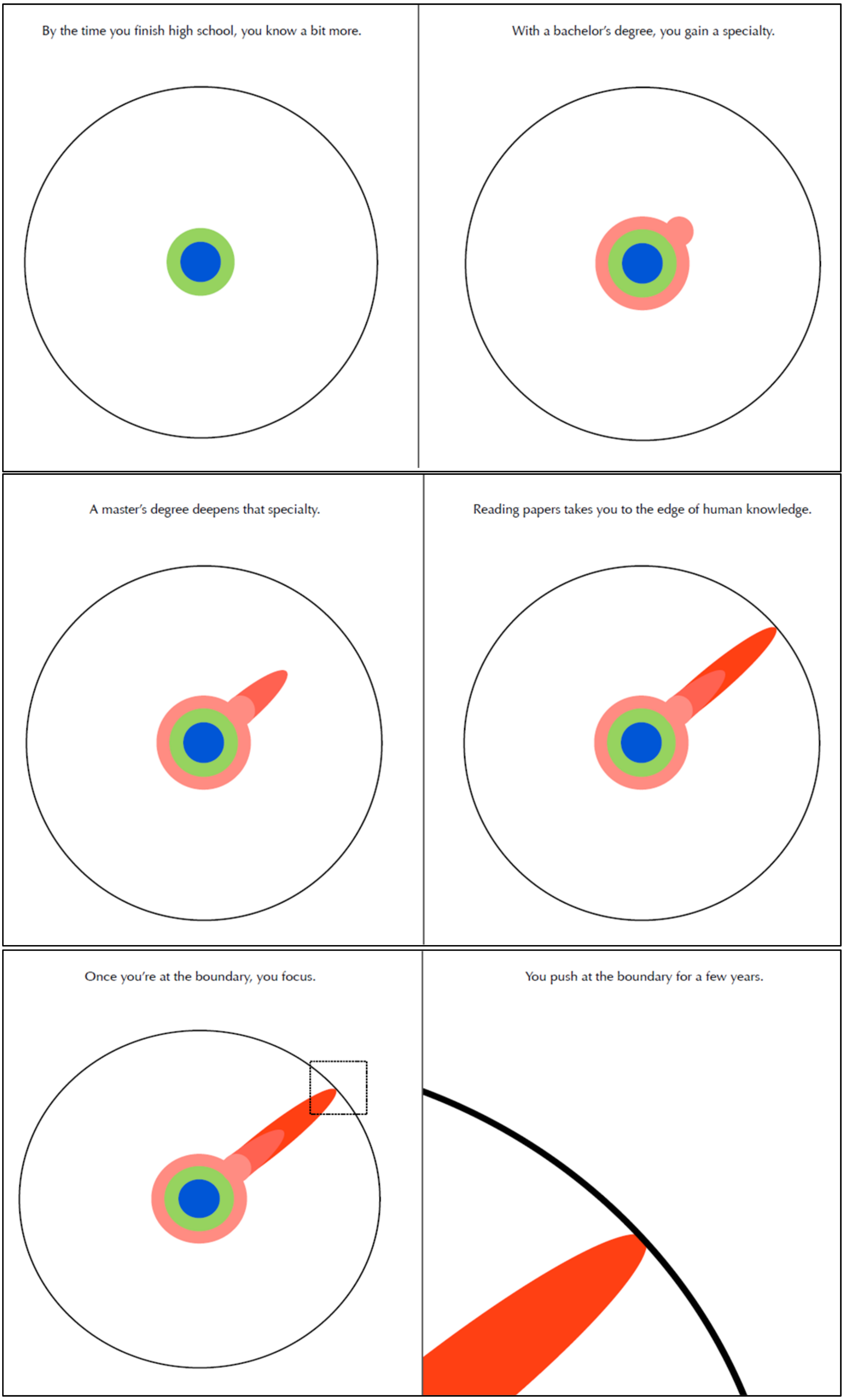
Finally, simulations on the efficiency of the risk-adjusted deposit insurance scheme show that our approach is in fact able to distinguish between risky and safe banks. Using elements from the two major strands of risk-adjusted deposit insurance, expected loss pricing and option pricing methods, we are hence able to incorporate more valuable information than current expected loss pricing methods while, in contrast to option pricing methods, relying on information that is readily available for most banks in developed economies.

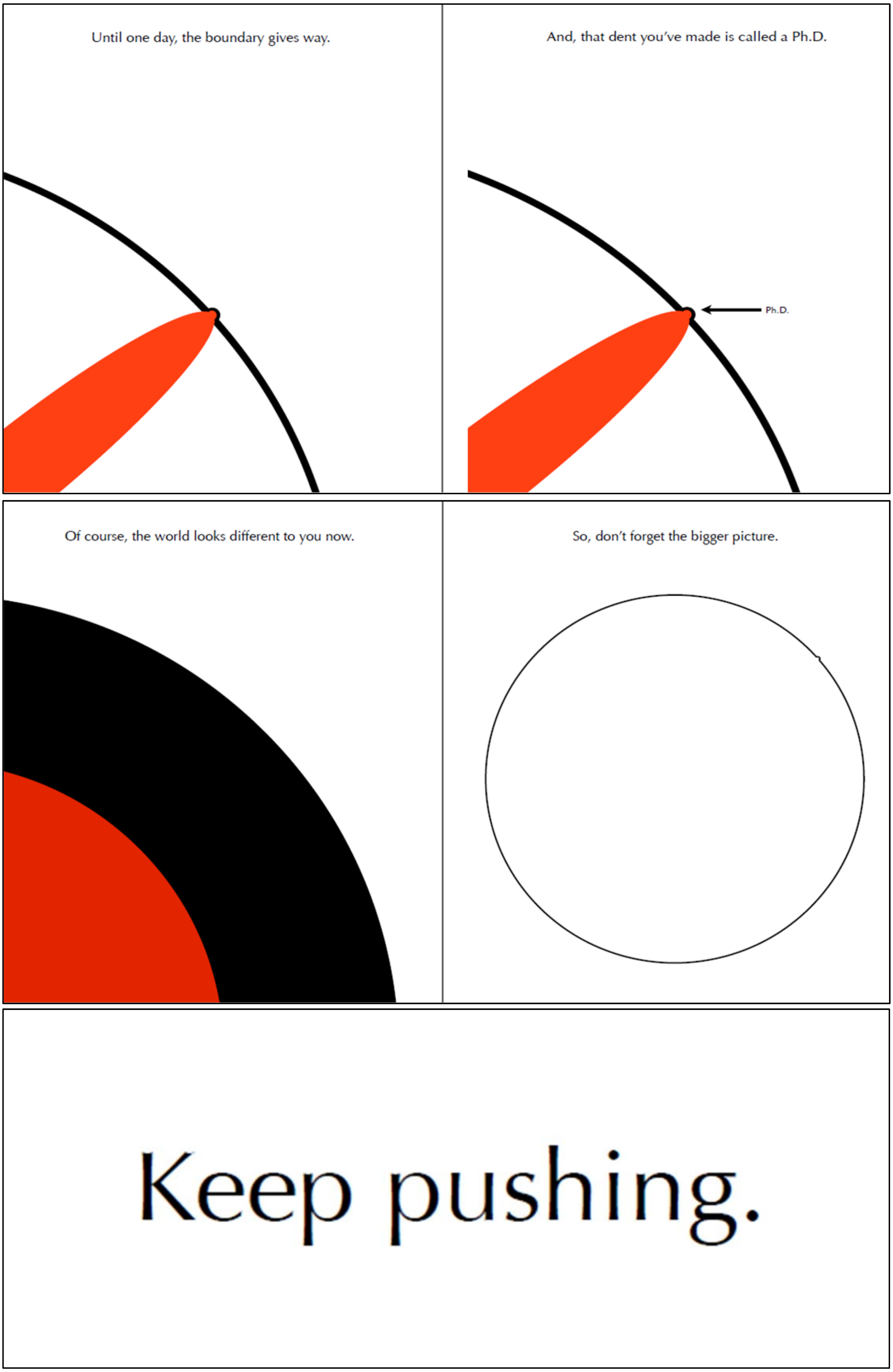
The four research projects try to shed light on causes and remedies of financial crises from three different angles. As the recent financial crises have once more forcefully demonstrated, research on financial stability is an open issue of academic progress. I hope that some of my insights help pushing our circle of knowledge at least a tiny bit further, which leads me to my final note: Where is my dent?

Figure 8-1: The Illustrated Guide to a Ph.D. by Matt Might

Source: http://matt.might.net/articles/phd-school-in-pictures




By the time you finish high school, you know a bit more.
With a bachelor's degree, you gain a specialty.
A master's degree deepens that specialty.
Reading papers takes you to the edge of human knowledge.
Once you're at the boundary, you focus.
You push at the boundary for a few years.


Until one day, the boundary gives way.
And, that dent you've made is called a Ph.D.
Ph.D.
Of course, the world looks different to you now.
So, don't forget the bigger picture.
Keep pushing.

References

Altman, E. (1968): “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy”, *Journal of Finance*, 23 (4), 589 – 610.

Barth, J., Caprio, G., and Levine, R. (2000): “Banking systems around the globe: Do regulation and ownership affect performance and stability?”, Conference on Prudential Supervision: What Works and What Doesn’t, National Bureau of Economic Research, January.

Bagehot, W. (1873): “Lombard Street: A Description of the Money Market”, Charles Scribner’s Sons, New York.

Beck, T., Demirguc-Kunt, A., and Levine, R. (2006): “Bank Concentration, Competition, and Crises: First Results”, *Journal of Banking & Finance* 30 (5), 1581 – 1603.

Beck, T. (2008): “Bank Competition and Financial Stability: Friends or Foes?”, Policy Research Working Paper Series 4656, The World Bank.

Bernet, B. and Walter, S. (2009): “Design, Structure and Implementation of a Modern Deposit Insurance Scheme”, SUERF – The European Money and Finance Forum, Vienna.

Bordo, M., Eichengreen, B., Klingebiel, D., and Martinez-Peria, M. (2001). “Is the Crisis Problem Growing More Severe?”, *Economic Policy* 16, 53–82.

Boyd, J. and De Nicolo, G. (2005): “The Theory of Bank Risk Taking and Competition Revisited”, *Journal of Finance* 60, 1329 – 1343.

Boyd, J., De Nicolo, G., and Jalal, A. (2006): “Bank Risk Taking and Competition: New Theory, New Empirics”, IMF Working Paper 06/297.

Bretschger, L., Kappel, V., and Werner, T. (2012): „Market Concentration and the Likelihood of Financial Crises”, *Journal of Banking & Finance*, forthcoming.

Caprio, G. and Klingebiel, D. (1997): „Bank Insolvencies: Cross-Country Experience”, Policy Research Working Paper, 1620, The World Bank, Washington.

Caprio, G., Klingebiel, D. (1999): “Episodes of Systemic and Borderline Financial Crises”, Mimeo. World Bank, Washington, DC.

Chan, Y., Greenbaum, S., and Thakor, A. (1986): “Information Reusability, Competition and Bank Asset Quality”, *Journal of Banking and Finance* 10, 243 – 253.

Chang, E., Guerra, S., Lima, E., and Tabak, B. (2008): “The Stability-Concentration Relationship in the Brazilian Banking System”, *Journal of International Financial Markets* 18 (4), 388 – 397.

Crockett, A. (2000): “Marrying the micro- and macro-prudential dimensions of financial stability”, speech at the financial stability forum, Basel.

Cukierman, A. (1992): “Central Bank Strategy, Credibility and Independence: Theory and Evidence”, MIT Press.

Diamond, D. and Dybvig, P. (1983): “Bank Runs, Deposit Insurance, and Liquidity”, *Journal of Political Economy*, 91, 401-419.

Dick, A. (2006): “Nationwide Branching and its Impact on Market Structure, Quality, and Bank Performance”, *Journal of Business* 79 (2), 567 – 592.

Demirguc-Kunt, A. and Detrigiache, E. (2002): “Does Deposit Insurance Increase Banking System Stability? An Empirical Investigation”, *Journal of Monetary Economics* 49 (7), 1373 – 1406.

Demirgüç-Kunt, A., Detragiache, E., and Gupta, P. (2006): “Inside the Crisis: An Empirical Analysis of Banking Systems in Distress”, *Journal of International Economics and Finance*, 25, 702–718.

Demirguc-Kunt, A., Laeven, L., and Levine, R. (2004): “Regulations, Market Structure, Institutions, and the Cost of Financial Intermediation”, *Journal of Money, Credit and Banking* 36 (3), 593 – 622.

Deutsche Bundesbank (2003): “Report on the Stability of the German Financial System,” Monthly Report, Frankfurt, December.

Evrensel, A. (2008): “Banking Crisis and Financial Structure: A Survival-Time Analysis”, *International Review of Economics & Finance*, 17 (4), 589 – 602.

Fisher, I. (1933): “The Debt-Inflation Theory of Great Depressions”, *Econometrica* 1 (4), 337-357.

Friedman, M. and Schwartz, A. (1963): “A Monetary History of the USA 1867-1960”, Princeton University Press, Princeton.

Garcia-Herrero, A. and Del Rio Lopez, P. (2012): “Financial Stability and the Design of Monetary Policy”, *Journal of International Money and Finance*, forthcoming.

Goldgar, A. (2007): “Tulipmania. Money, Honor, and Knowledge in the Dutch Golden Age”, The University of Chicago Press, Chicago.

Gupta, P. (1996): “Currency Crises, Banking Crises and Twin Crises: A Comprehensive Review of the Literature, Mimeo, International Monetary Fund.

Hoggarth, G., Ries, R., and Saporta, V. (2002): “Costs of Banking System Instability: Some Empirical Evidence”, *Journal of Banking and Finance*, 26, 825 – 855.

Honohan, P., Klingebiel, D. (2000): “Controlling Fiscal Costs of Banking Crises”, Mimeo, World Bank.

Hutchinson, M. and Noy, I. (2005): “How Bad are Twins? Output Costs of Currency and Banking Crises”, *Journal of Money, Credit, and Banking*, 37 (4), 725 – 752.

International Monetary Fund (1998): “Financial Crises, Characteristics and Indicators of Vulnerability”, *World Economic Outlook*, 4.

International Monetary Fund (1999): “From Crisis to Recovery in the Emerging Market Economies”, *World Economic Outlook,* 2.

Issing, O. (2003): “Monetary and Financial Stability: Is there a Trade-Off”, Conference on Monetary Stability, Financial Stability and the Business Cycle, Bank for International Settlements, Basel.

Jiménez, G., Lopez, J., and Saurina, J. (2007): "How Does Competition Impact Bank Risk-Taking?" Federal Reserve Bank of San Francisco Working Paper Series 2007-23.

Kaminsky, G., Reinahrt, C. (1999): "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems", *American Economic Review*, 89, pp. 473-500.

Keeley, M. (1990): "Deposit Insurance, Risk and Market Power in Banking", *American Economic Review* 80, 1183 – 1200.

Kindleberger, C. (1978): "Manias, Panics, and Crashes: A History of Financial Crises", Basic Books, New York.

Klingebiel, D. (2000): "The Use of Asset Management Companies in the Resolution of Banking Crises", World Bank Policy Research Paper 2284.

Laeven, L. and Valencia, F. (2008): "Systemic Banking Crises: A New Database", IMF Working Paper 08/224.

Laeven, L. and Valencia, F. (2010): "Resolution of Banking Crises: The Good, the Bad, and the Ugly", IMF Working Paper 10/146.

Laeven, L. and Valencia, F. (2011): "The Real Effects of Financial Sector Interventions During Crises", IMF Working Paper 11/45.

Lindgren, C., Garcia, G. and Saal, M. (1996): "Bank Soundness and Macroeconomic Policy", International Monetary Fund.

Leijonhufvud, A. (2007): "Monetary and Financial Stability", CEPR Policy Insight, 14, 1-9.

Marcus, A. (1984): "Deregulation and Bank Financial Policy", *Journal of Banking and Finance* 8, 557 – 565.

Matutes, C., Vives, X. (2000): "Imperfect Competition, Risk Taking, and Regulation in Banking", *European Economic Review* 44 (1), 1-34.

Mishkin, F. (1996): "Understanding Financial Crises: A Developing Country's Perspective", NBER Working Paper 5600, Cambridge Massachusetts.

Mishkin, F. (1999): “Global Financial Instability: Framework, Events, Issues,” *Journal of Economic Perspectives* 13, pp. 3–20.

Mitchell, W. (1941): “Business Cycles and Their Causes”, University of California Press, Berkeley.

Morkoetter, S., Schaller, M., and Westerfeld, S. (2012): „Liquidity Dynamics of Bank Defaults”, *European Financial Management*, forthcoming.

Norwegian Central Bank (2003): “Financial Stability Review”, February, 2003.

Padoa-Schioppa, T. (2002): “Central Banks and Financial Stability: Exploring Land in Between”, Second ECB Central Banking Conference, Frankfurt am Main, October 2002.

Rajan, R. and Zingales, L. (2003): “Saving Capitalism from the Capitalists”, Crown Business Division of Random House, New York.

Rajan, R. (2010): “Fault Lines – How Hidden Fractures Still Threaten the World Economy”, Princeton University Press, Princeton.

Reinhard, C. and Rogoff, K. (2009): “This Time is Different: Eight Centuries of Financial Folly”, Princeton University Press, Princeton.

Rochet, J. (2008): “Why Are There So Many Banking Crises?”, Princeton University Press, Princeton.

Ruiz-Porras, A. (2007): “Banking Competition and Financial Fragility: Evidence from Panel-Data”, MPRA Paper 5673, University Library of Munich, Germany.

Schwart, A. (1995): “Systemic Risk and the Macroeconomy”, G. Kaufman (ed.), Banking Financial Markets and Systemic Risk, Research in Financial Services, Private and Public Policy, 7, JAI Press, Hampton.

Segal, S. (2004): “*Die Botanik der Tulpe”,* in: André van der Goes (ed.): Tulpomanie. Die Tulpe in der Kunst des 16. und 17. Jahrhunderts. Uitgeverij Waanders, Zwolle 2004.

Shiller, R. (2003): “The New Financial Order: Risk in the 21st Century”, Princeton University Press, Princeton.

Shiller, R. (2012): “The Subprime Solution: How Today’s Global Financial Crisis Happened, and What to Do about it”, Princeton University Press, Princeton.

Uhde, A. and Heimeshoff, U. (2009): “Consolidation in Banking and Financial Stability in Europe: Empirical Evidence”, *Journal of Banking and Finance* 33, 1299 – 1311.

Curriculum Vitae

Matthias Schaller

Address	Rablstrasse 38, 81669 Munich, Germany
Phone	+49 (175) 277 52 84
E-Mail	matthias.schaller@unisg.ch
Date of Birth	March 8th, 1984
Place of Birth	Munich
Nationality	German

Education

Feb. 2012 – July 2012

Visiting Scholar
University of Illinois at Urbana-Champaign, Illinois, USA
Prof. Charles Kahn
Grant of the Swiss National Fund

July 2011

Barcelona Banking Summer School
Graduate School of Economics, University of Pompeu Fabra, Barcelona, Spain

Since Feb. 2009

Ph.D. Candidate in Business Administration with a focus on Finance
University of St. Gallen, Switzerland
Title: „Aspects of Stability in the Financial Sector"
Referees: Prof. Beat Bernet & Prof. Martin Brown

Oct. 2003 – Sept. 2008

Technology- and Management-based Business Administration
Technical University of Munich, Germany
Major in Financial Management and Entrepreneurial Finance, Minor in Electronics and IT
University degree comparable to M. Sc.:
Diplom-Kaufmann (Univ.), Grade 1.4 (1:best to 5: worst)

Jan. 2006 – May 2006

Exchange Student
Oklahoma State University, Oklahoma, USA
GPA: 4.0 (4: best to 1: worst)

Sept. 1994 – June 2003

Allgemeine Hochschulreife
Oskar-von-Miller Gymnasium, Munich, Germany
Diploma from German Secondary School qualifying for University Admission
Grade: 1.9 (1: best to 6: worst)

Publications

European Financial Management, forthcoming (2012)

Morkötter, S., Schaller, M., Westerfeld, S.: "Liquidity Dynamics of Bank Defaults".

New Paradigms in Banking, Financial Markets and Regulation, SUERF Study 2012/2.

Schaller, M., Walter, S.: "An Alternative Way of Calculating Pragmatic Risk-based Deposit Insurance Premiums".

Die Bank, Nr. 2, pages 40-45 (2011)

Schaller, M. Westerfeld, S.: "Schicksal oder Verhandlung? KMU im Kreditprozess bei Banken".

Conferences

June 2011	International Colloquium for Ph.D. Candidates in Banking, University Liechtenstein, Vaduz.
May 2011	29th SUERF Colloquium, Brussels, Belgium.
April 2011	14th Conference of the Swiss Society for Financial Market Research, Zurich, Switzerland.
September 2010	CEQURA Conference on Advances in Financial and Insurance Risk Management, Munich, Germany.

Professional Experience

Since Feb. 2009	**Research Assistant** *Chair for Banking, University of St. Gallen, Switzerland* Prof. Beat Bernet & Prof. Martin Brown
March 2007 – Dec. 2007 Oct. 2005 – Dec. 2005	**Intern / Working Student** *Golding Capital Partners, Munich, Germany* Private Equity Fund-of-Funds: Fund Selection and Due Diligence
Nov. 2004 – Nov. 2005	**Working Student** *o2 AG, Munich, Germany* Telecommunication: Division for Corporate Quality
Sept. 2004 – Oct. 2004	**Working Student** *Softlab GmbH (now: Cirquent), Munich, Germany* IT-Consulting: Division for Supply Chain Management

Additional Skills

Languages	German (mother tongue) English (fluent) French, Spanish, Latin (Basic Knowledge)
Software	Microsoft Office, Lotus Notes Statistical Programs: Stata, SPSS, Matlab
Interests	Travelling, Cooking, Soccer, Tennis