Stockholm School of Economics

Bachelor´s Thesis in Finance, Spring 2015

Diminishing Risk-Weights Under the Basel II Accord: A Sign of Better Credit Quality or Regulatory Arbitrage?

A Study on European Banks That Have Utilized Internal Ratings Based Approaches for Credit Risk Assessment Between 2007 and 2014

Erik Boltenstål[1] Markus Falkman[2]

Abstract: The Basel II-accord aimed to strengthen the financial system by making the banks more solvent. The Internal Ratings Based-model was introduced to create a better connection between risk held and regulatory capital. But during the last eight years, the average credit rating for the largest European banks has fallen to a level just three steps above speculative grade. This paper aims to study this anomaly. We have used data from 57 of the largest European banks and compared their risk-weights to market measures as well as accounting measures of credit risk. Our findings include statistically significant deviations in the relationship between risk-weights and credit risk. We argue that risk-weights do not reflect credit risk properly and that more advanced Internal Ratings Based-models systematically underestimate actual credit risk. Our arguments are founded on the deteriorating credit ratings of the European banks and their diminishing risk-weights. There is what appears to be a fundamental dichotomy between the banks' own perception of risk and that of the market.

Keywords: Basel II, model based approach, risk weights, capital requirements, regulatory arbitrage, credit ratings

JEL Classification: G20, G21, G28

Tutor: Ramin Baghai

Acknowledgements: We would like to thank our tutor Ramin Baghai for valuable feedback and guidance. We would also like to thank Per-Olov Edlund for helpful input regarding the statistical methods used in this thesis.

[1] 22790@student.hhs.se
[2] 22850@student.hhs.se

Contents

1. Introduction

Since the Basel II Accord was implemented in most major European economies in early 2008, it has had a fundamental impact on how financial institutions assess their risk. The accord has introduced market risk and operational risk into the process of determining the minimum capital requirements for financial institutions – in addition to the major risk bucket of credit risk, which is the only risk considered by the Basel I Accord. But the new framework also included more sophisticated methods for measuring credit risk, which is the main topic of this thesis.

The new models to assess credit risk were developed to ensure that capital allocation decisions would be more risk sensitive than before. This was done by introducing Internal Ratings Based (IRB) models for risk assessment, where banks and other financial institutions could do their own risk estimates for their exposures, given that they received approval for their internal models from their domestic Financial Supervisory Authority.

Under these new rules, the risk-weights have become an important topic due to the discrepancies there are between different countries and even between different banks. This is largely due to a shift by the larger banks from standardized models based on external credit ratings, to internal models based on internal ratings. Risk-weights have decreased for each year, while credit ratings have deteriorated for practically all European banks. These are two very inconsistent observations, since lower risk-weights should imply better credit quality of the banks´ exposures, i.e. lower credit risk. There is what appears to be a fundamental dichotomy between the banks' own perception of risk and that of the market – which is the main issue that this paper aims to investigate.

Recent research papers on this subject such as Mariathasan and Merrouche (2012), Behn et al. (2014) and Acharaya et al. (2014) suggest that the decline in risk-weights are due to a strategic use of the internal models by the banks to achieve artificially low capital charges not reflecting actual risk. The same research also implies that the internal models are constructed in a way that provides incentives for the banks to manipulate inputs to the model. These claims are the foundation of our two formulated hypotheses:

Hypothesis 1: The overall diminishing risk-weights do not correspond to an increase in credit quality among banks' exposures.

Hypothesis 2: The more regulatory discretion banks are given in using advanced models, the less calculated risk-weights will correlate with market and accounting measures of credit quality.

We have compiled a dataset including 57 of the largest banks in Europe, consisting of eight years of panel data from 2007 to 2014. We elected to limit the study to Europe due to the largely different and more staggered implementation of Basel II in the United States. Unlike the papers by Mariathasan and Merrouche (2012) and Behn et al. (2014) we have focused on comparing the risk-weights to different market measures of credit risk. We have used two primary market measures, CDS-spreads and external credit ratings. These measures provide us with a third party (market) opinion of the credit quality of the banks' exposures. This allows for a comparison between the banks' risk-weights and a reasonably unbiased measure of the actual credit risk held by the banks. We expect to see a steady decline in average risk-weights in our sample that is not explained by improved credit ratings or less risk held by the banks. We also use accounting measures of risk such as non-performing loans and net loan losses to proxy for credit risk.

Our findings are consistent with the previous research on the subject. We find that the risk-weights have declined by over 21% on average between 2008 and 2014 in our sample. During the same period, credit ratings have declined from an average of AA in 2008 to an average of BBB+ in 2014 (S&P´s rating) for the same sample – representing a decline of five steps on the credit rating scale. At the same time net loan losses have more than doubled and non-performing loans have increased tenfold. Moreover, the banks in our sample appear to be aware of the increased riskiness of their exposures, since their reserves for loans losses have also doubled. However, this is not reflected in the risk-weights. We also find that risk-weights are consistently lower for IRB portfolios than for Standardized approach portfolios in our sample – implying either that; (1) the Standardized approach-model is overestimating risk, or that (2) the IRB-model is underestimating risk. This supports our second hypothesis that IRB-models are producing artificially low risk-weights.

Our regressions confirm a positive relationship between total risk-weights and our credit rating index, and a negative relationship between total risk-weights and CDS-spreads. These results provide further support to our first hypothesis. We confirm the findings of Merrouche (2012) and Behn et al. (2014) that the lower risk-weights indeed seem to be a case of regulatory arbitrage in the form of risk-weight manipulation - resulting in artificially low risk-weights that are not necessarily in line with how the market prices the risk.

We believe that this comparison, while standing on the shoulders of previous papers, could provide more relevant evidence that the IRB-models do not work as intended. With Basel IV just around the corner it is a very topical subject. Especially since Basel IV in its current form suggests the return to more standardized approaches for calculating capital requirements as well as better disclosure of the calculations.

The outline of this paper will be as follows. Section 2 will provide a background to the Basel II framework, as well as review the previous literature on this subject. Section 3 will describe the dataset that we have used for the study. Section 4 will provide a description of the variables we have used and why they have been included, as well as an outline of our empirical strategy approaching this study. Our main findings will be presented in section 5, including descriptive statistics and regressions of risk-weights against our measures of credit risk. We will also discuss the implications of the results in this section, test the robustness of our model and consider possible selection biases. Section 6 will provide the reader with the conclusions of the study in a condensed manner. The last section of the paper, section 7, is devoted to discussing limitations of the research conducted and suggestions for future research.

2. Background

2.1 The Basel II Framework

The Bank for International Settlements (BIS) was founded in 1930, and is the world's oldest international financial organization. The overall purpose of BIS is to serve central banks in their work towards monetary and financial stability. The Basel II Accord was first published by the Basel Committee on Banking Supervision (an organ of BIS) in 2004, but was implemented in most European economies during 2007 and 2008. It focuses on connecting the amount of regulatory capital the banks must hold to the riskiness of the assets in the banks' portfolios. Meaning that the riskier loans a bank holds, the more regulatory capital it has to hold making the bank more solvent but also making riskier loans more expensive (Lind, 2005).

The Basel II Accord is built on three pillars, the first concerning the minimum capital requirements of all banks, and more specifically that the regulatory capital has to be at least 8% of total Risk-Weighted Assets (RWA). While Basel I only included credit risk, Basel II adds market risk and operational risk to the equation. All the formulas as described in section 2.1-2.3 are disclosed by the Basel Committee on Banking Supervision in their Basel II framework reports (1988, 2004, 2006). The minimum levels of regulatory capital for Basel I and II are displayed below in the equations (2.1.1) and (2.1.2)

Basel I rule:

$$\frac{Capital\ Requirement}{RWA_{Credit}} \geq 8\% \qquad (2.1.1)$$

Basel II rule:

$$\frac{Capital\ Requirement}{RWA_{Credit} + (MRC_{Market} * 12.5) + (ORC_{Opr} * 12{,}5)} \geq 8\% \qquad (2.1.2)$$

The economic capital that the banks hold to cover the capital requirements is divided into different Tiers, where

- Tier-1 is the "core capital" that should cover the majority of the risk, i.e. equity, fully paid common stock etc.);
- Tier-2 is the "supplementary capital" that can consist of undisclosed reserves, provisions, or loan loss reserves;
- Tier-3 can only be used to cover market risk and can consist of short term subordinate exposure.

The second pillar is a way of ensuring that the banks are following Pillar 1 by having adequate economic capital to cover the regulatory minimum. The domestic Financial Supervisory Authority (FSA) is involved in this process, since it is their job to scrutinize banks and their risks. Two processes are central to the second pillar. The first one is the Internal Capital Adequacy Assessment Process (ICAAP) where the banks themselves asses their capital adequacy and risk profiles, but also perform stress tests and scenario analyses. The second being the Supervisory Review and Evaluation Process (SREP) which is an independent evaluation of the ICAAP by the domestic FSA. The domestic FSAs often collaborate with foreign FSAs, the European Banking Authority (EBA) and the European Central Bank (ECB) when it comes to the SREP.

The third pillar is an articulate demand on banks to disclose information regarding their capital structure and their actual economic (Tier-1 and Tier-2) capital they have available to cover the regulatory minimum requirements. The result of the pillar 3 requirements is a standalone report called “Pillar 3 Disclosure” which is published by the banks on an annual basis.

2.2 The Standardized Approach (SA)

The Standardized approach (SA) to calculate RWA for credit risk is structured around predetermined Risk-Weights (RWs) assigned to exposures of different credit qualities. The RWs are different for different types of exposures. Sovereign exposures are for instance given a RW of 0% if they are rated AAA to AA- (S&P rating), compared to corporates where the same rating would yield a RW of 20%. The tables below illustrate the different RWs assigned to different sovereign and corporate exposures.

2.2.1 Risk-weights for sovereign exposures

Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to BB-	Below B-	unrated
RW	0%	20%	50%	100%	150%	100%

2.2.2 Risk-weights for corporate exposures

Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BB-	Below B-	unrated
RW	20%	50%	100%	150%	100%

When the appropriate RW is determined, the capital requirement for the claim is calculated using the following formula

$$Capital\ Requirement = K * RW * EAD \qquad (2.2.1)$$

where K is the Capital Requirement percentage of 8%, RW is the assigned Risk-Weight, and EAD is the Exposure at Default.

2.3 The Internal Ratings Based Approach (IRB)

Under the Internal Ratings Based Approach (IRB), banks can use their own internal estimates of some inputs to the model that will determine the capital requirement for a certain exposure. The capital requirements should be set so that it takes into account both the Expected Loss (EL) and the Unexpected Loss (UL), but not extremely unlikely tail events in which case holding regulatory capital would be too expensive (see figure 2.3.1) (Hasan & Zazzara, 2006).

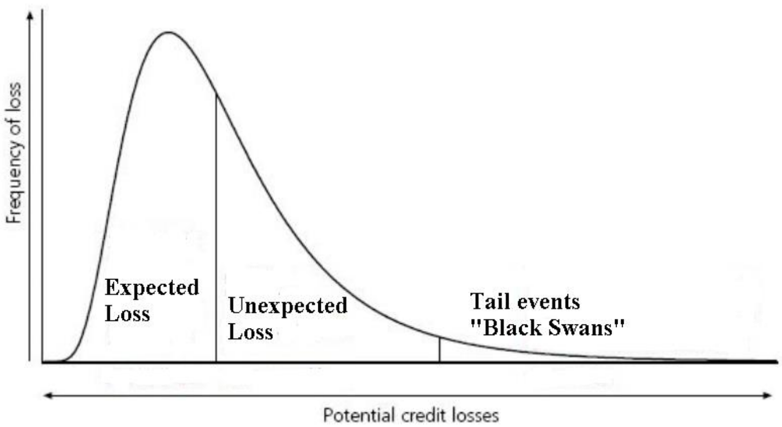


Figure 2.3.1 – Expected losses, *this graph illustrates the Expected Loss (EL) and the Unexpected Loss (UL) plotted as frequency of loss against the potential credit loss. The more extreme potential credit losses are very unlikely and sometimes called tail events or "Black Swans".*

The expected loss can be calculated using a formula, where the inputs are Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD).

$$EL = PD * LGD * EAD \qquad (2.3.1)$$

The capital requirements (K) in percent are calculated using a formula provided to the banks by the Basel Committee. There is some slight adjustments to the formula for different types of exposures, but the general formula is the following

$$K = \left[LGD * N\left[(1-R)^{-0.5} * G(PD) + \left(\frac{R}{1-R}\right)^{0.5} * G(0.999)\right] - PD * LGD\right] * (1 - 1.5 * b)^{-1} * (1 + (M - 2{,}5) * b) \tag{2.3.2}$$

Where $N(x)$ denotes the cumulative distribution function for a standard normal random variable, and $G(z)$ denotes the inverse cumulative distribution function for a standard normal random variable. The inputs' asset correlation (R) and the maturity adjustment (b) are calculated using the following formulas

$$R = 0.12 * \frac{1 - EXP(-50 * PD)}{1 - EXP(-50)} + 0.24 * 1 - \frac{1 - EXP(-50 * PD)}{1 - EXP(-50)} \tag{2.3.3}$$

$$b = (0.11852 - 0.05478 * \ln(PD))^2 \tag{2.3.4}$$

When the Capital Requirement (K) is calculated, the RWA can be calculated using the same formula as in the Standardized approach

$$RWA = K * EAD * 12.5 \tag{2.3.5}$$

While the formula for calculating regulatory capital is the same for all banks, the inputs in the form of PD, LGD, EAD and M can all be determined using internal estimates.

2.3.1 The Foundation IRB Approach

Banks using the Foundation IRB approach can only do internal estimates of their PDs. This is done using advanced statistical models using historical default rates as inputs. The PDs can also be changed as a result of specialist knowledge or experience about a specific exposure, which enables manipulation of risk-weights.

2.3.2 The Advanced IRB Approach

Banks that use the Advanced IRB approach can use internal estimates for PD, LGD, EAD and M. This gives the banks an even greater opportunity to affect their capital charges, although these models are also harder to get approved by the FSA. Both models can be used at the same time but for different exposures, even in combination with the Standardized model. The only limitation is that when a portfolio is approved for the use of IRB-models, the bank cannot switch back to the Standardized approach for that specific exposure under current rules.

2.4 Incentives to Underreport Risk-Weights

The reasons as to why a bank would purposely underreport RWs are complex, and often the arguments presented are fallacious. The argument most often mentioned is that the banks can achieve a higher Return on Equity (ROE) by having lower capital requirements and thus a higher leverage ratio. The higher the RWs, the more regulatory capital has to be held in the bank instead of being lent to someone else where it could be generating income. This argument is however fallacious, since a higher ROE comes at a higher risk, and thus not increasing the risk-adjusted return. As Amati et al. (2013) argue, it is incorrect to treat the ROE requirements as fixed when the equity increases due to higher capital requirements. The often cited argument that increased capital requirements would restrict the banks´ lending activity, is based on fallacious logic that the only way for a bank to recapitalize in response to higher capital requirements is to reduce their liabilities. This is however not the case, since the bank could just as well issue more equity and use the proceeds to reduce their debt. This would reduce the leverage without reducing the size of the balance sheet. There is however, another underlying mechanism that explain why bank managers and shareholders are so unwilling to reduce the leverage of the firm, namely the leverage ratchet effect. The effect is a result of debt overhang, meaning that the shareholders have few incentives to delever a highly levered firm, and are likely to make bad decisions for the firm since the majority of proceeds from positive NPV projects will go to debtholders. The result is that shareholders and managers try to justify excessive risk taking by fallacious arguments as the one mentioned above. The real explanation to the underreporting of RWs is hence that the managers and shareholders have incentives not to reduce leverage, even though it would not affect the size of the bank´s balance sheet or its lending capabilities.

Another argument is that the IRB-models incur high compliance costs for the banks who wish to use them, why the banks would not go through costly procedures of getting approval for these models if they did not think that it was a positive NPV investment (Behn, 2014). This is however partly an incorrect assumption, since a debt overhang problem could very well make the managers and shareholders willing to take on excessive risk to increase their expected payoff – even though the project is suboptimal for the firm as a whole.

The overall conclusion has to be that it is the shareholders and their appointed managers that have incentives to underreport risk-weights, rather than the bank as whole including debtholders. We will however assume this distinction to be implicit when we refer to banks incentives to underreport risk-weights in the following sections.

2.5 Literature Review

We have now covered the background as to why the banks' shareholders and management have incentives to underreport their RWs. The IRB-model introduced under Basel II was the perfect tool to manipulate RWs, not being restrained by external ratings anymore. The topic concerning the actual manipulation of these internal models is however fairly new, and there is not a vast selection of literature in this area. Much of the literature is not academic in nature and written by organisations such as the Bank for International Settlements (BIS), the International Monetary Fund (IMF) or the European Banking Authority (EBA). Reports produced by these organisations have mainly been interested in the fact that there seems to be large discrepancies between different countries and even between different firms in the same country when it comes to RWs (Le Leslé & Avramova, 2012), (European Banking Authority, 2013a, 2013b, 2013c, 2014) and (Basel Committee on Banking Supervision, 2013).

Although we will touch on the regional differences when it comes to RWs, our main focus in this paper will be on how different modeling approaches affect them. There seems to be a consensus in the academic literature that actual credit risk is seldom reflected properly in RWs among large banks, and that manipulation is not only is possible but a very real concern.

Behn et al. (2014) discusses the practical consequences of advanced model-based regulation and the IRB-model in particular. The study uses a sample of 1600 German banks, out of which 45 used IRB-models. Their main findings are that IRB banks have incentives to report lower RWs in order to increase their margins by lowering capital charges, and especially so for their low-risk portfolios. This is due to the non-linearity of the relationship between RWs and probabilities of default (PD). Very small changes in PDs will have a large impact on the RWs of low-risk exposures as is evident in the diagram they present, see (Figure 2.5.1). This also implies that increasing the probability of default quite substantially for already risky exposures will only have small effects on the RWs, which is the essence of why banks have incentives to shift their riskier exposures to IRB-models. The reason why the SA model is still used for extremely safe sovereign exposures is that they are already assigned a RW of 0%. In conclusion, this means that the banks gain the most from manipulating low-risk corporate and retail portfolios, but also have incentives to shift their riskiest portfolios to the IRB-model.

Behn et al. (2014) also find that the lower RWs among IRB-portfolios compared to SA-portfolios do not correspond to lower default rates, but rather the opposite. Furthermore they find that the average interest rate is higher for IRB loans than for SA loans, implying that the banks are aware of the higher risk these exposures carries, but purposely underreport the RWs. All the findings are especially prominent for AIRB portfolios. The overall conclusion is that the advanced IRB models do not work as intended, and systematically underestimate risk. The authors suggest simpler rules for determining capital requirements, in line with the Standardized approach, in order to remedy the diminishing levels of regulatory capital.

Mariathasan and Merrouche (2012) discuss the incentives for banks to underreport and manipulate RWs. They base their research on comparisons between the risk-weighted and unweighted capital ratios and how these compare in predicting default. In better times the risk-weighted ratios work as a good tool for predicting risk of default. However, in economic downturns, the unweighted capital ratios work better. They draw the conclusion that banks optimize their RWs in order to achieve lower capital charges, and that it is especially monopolistic and weakly capitalised banks that seem to engage in this behaviour – which is consistent with our previous reasoning about how debt overhang can create incentives for banks to underreport RWs. They also note that the underreporting of RWs seems to be especially prominent in economic downturns, which could be a sign of fear of government intervention or nationalisation.

Becker and Opp (2013) investigate how the reformed capital requirements for insurance companies' holdings of mortgage-backed securities affected the level of regulatory capital held. The reform that took place replaced the third party ratings of these securities which are paid for by the issuer with a new measurement, expected loss, paid for by the regulators. The authors conclude that the greater discreation given to insurance companies to calculate their capital requirements, resulted in that the capital requirements declined to a fraction of what they would have been under the previous framework. The authors discuss possible reasons for why the regulators chose to implement this reform. One of their theories is that it was not a matter of increasing the solvency of insurance companies, but rather the contrary, a way to provide capital relief. If the old system with external ratings had remained, the capital requirements would have increased significantly since mortgage-backed securities were being downgraded across the board at the time (2009). Therefore the new system was implemented to hinder firesales and a new crash. This paper is highly relevant for our research, even though it does not concern banks.

Hellwig (2010) argues for a complete overhaul of the current banking regulation, raising capital requirements substantially. The argument is built on the observation that the current internal models used in banks lead to undercapitalization, and specifically points out this as a key factor that allowed banks to be undercapitalized before the crisis in 2007/2009.

The author argues that the current rules have no thoeretical foundation, and that they systematically underestimate risk.

Acharaya et al. (2014) looks at macroprudential stress tests, such as those conducted by the EBA, and compares how balance-sheets and market data on projected losses compare to actual losses. The authors find that these coincide surprisingly well. The capital requirements of banks however, is found to be inadequate *ex post* compared to market data. They conclude that this dichotomy is due to a overreliance on regulatory RWs as determinants for capital requirements.

In summary, the majority of academic papers in this area seem to advocate simpler rules, higher capital requirements and increasing transparency when it comes to banking regulation. This is consistent with the findings of Glaeser and Schleifer (2001), that complex regulation imposes an enforcement cost on society, as well as a compliance cost on regulated entities – giving incentives to the regulated entities to engage in regulatory arbitrage. It is also consistent with the current consensus on the regulatory side, since the proposed Basel IV framework will most likely go back to less advanced methods to prevent regulatory arbitrage among large banks.

3. Data

3.1 Manually Collected Primary Data

The dataset consists of unbalanced, longitudinal panel data from 57 European banks over the years 2007-2014. The banks that are included in the dataset are disclosed in the tables section (Table 3.1.1). The selection of the banks has been done with consideration to their asset size in the sense that we have chosen the largest banks in Europe. The reason we aimed for the larger banks was the availability of data. The larger banks tend to use the advanced internal models to a larger extent due to their ability to handle large compliance costs. The larger banks also make their reports available in English more frequently and keep online archives. The market data is also more readily available. Smaller cooperative or privately held banks can not always be found in Reuters Datastream, Bloomberg or at the other large suppliers of data. The issuing of Credit Default Swaps (CDS) is also less frequent when it comes to the smaller banks, a fact that would pose a major problem should we use too small banks in our dataset. This is due to the fact that our method uses CDS-spreads as a market measure of risk, and their availability is important for our empirical strategy.

We have also considered the main exposure types of the banks in the sense that they have to have corporate lending as a major part of their total exposures. The reason we elected to focus on corporate lending and average total RWs is because this is where we expect to find the most prominent evidence of diminishing RWs. Moreover, the retail and sovereign exposures are included implicitly in the variable IRBtotal and RWtotal, but not as standalone data.

The banks in the dataset are located in Western Europe, many of them in the EMU-region but also in the Nordics, the UK and Switzerland. We chose to exclude US banks since the implementation of the Basel II framework differed from that in the EU. The implementation was drawn out with Basel I and II running in parallel for some time. In the EU the implementation took place through the Capital Requirements Directive (CRD) which basically turned Basel II into legislation for the member states from the beginning of 2007. Switzerland and Norway implemented Basel II at the same time.

The RW data is presented in each bank's yearly Pillar 3 disclosure, also commonly referred to as Risk Report, Risk Management Report or Capital Adequacy Report. This data has been collected manually, meaning that we have retrieved the data from the banks' pillar 3 disclosures published on their websites. It consists of several variables, disclosed in the tables section (Table 3.1.2). The RWs are presented as a percentage, and are the weighted average RWs for the corporate and total portfolios respectively. Since there are several different approaches (Standardized, Foundation IRB and Advanced IRB) to calculate the RWs, we present them as individual variables.

EAD or Exposure at Default is a variable that the banks use in their RW calculation. It represents the potential losses in the event of a defaulting client. We have included it here to be able to track which approach (FIRB, AIRB, SA) is most commonly used and if it changes over time. The EADs are in local currency but for comparison and trends we use ratio variables. These disclose the ratio of the EAD under each approach as a ratio of total EAD.

Not every bank utilizes every approach. The time series stretches from 2007, when the first banks started using RWs, to 2014. But not every bank has used all approaches during this whole time. Some banks start using more advanced approaches later and others shift towards only using the advanced methods. At the time of writing not all banks had disclosed their figures for 2014.

3.2 Secondary Data from Datastream, Bloomberg and Mint

The market data in the form of CDS-spreads has been collected from Reuters Datastream. The CDS-spreads are calculated using a suitable benchmark chosen by Datastream. It should not matter if it is the same benchmark for all banks or not since we do not intend to compare them. The CDS measure we have used is the 5-year, Euro, Senior Unsecured, Modified Modified Restructuring. The reason for this is that the 5-year CDS is the most commonly occurring and we chose Modified Modified Restructuring because we found that to be the preferable type used in Europe.

The balance sheet information and ratios (total assets, loan losses, non-performing loans and reserves for loan losses) have been collected through Datastream and Mint. The main source has been Datastream, but Mint has been used as a complement to those companies, mostly private, where Datastream has not been able to deliver any data.

The ratings from Moody’s and Standard and Poor’s were collected through Bloomberg. We collected every available rating from Moody’s, Standard and Poor’s and Fitch and then filtered for relevance, and occurrence over the time span 2007-2014. In the event of multiple rating changes in one year we only used the last rating that year.

4. Methodology

In this chapter we aim to describe how we performed our research. We have divided it into two sections; variable description and empirical strategy.

4.1 Variable Description

The variable $CDSspread$ is one of our two main dependent variables, and meant to serve as a market measure for risk, i.e. how the market values a specific bank's risk. Should a bank's credit risk be high, the risk of default increases. This will be reflected in the spread over the benchmark. The benchmarks are chosen by Datastream and not disclosed. They are most likely based on regions, maturity, seniority and type of reconstruction. One common benchmark is the LIBOR rate, but since we use a firm fixed effects model, it should not matter for our result which benchmark that is used in each case.

The second market measure of risk we have included as a dependent variable is an index of credit ratings. The index is comprised of an average of the following credit ratings, of which three are ratings from Moody's

- Long Term Bank Deposits, local currency ($LTBD$)
- Bank Financial Strength (BFS)
- Senior Unsecured Debt (SUD)

And one from Standard and Poor's

- Long Term Local Issuer, local currency ($LTLI$)

The ratings were translated to discrete numeric variables with a scale of 1-21, where 1 is a C or D rating at Moody´s and S&P respectively, and 21 is a Aaa or AAA rating at Moody´s and S&P respectively (Table 4.1.1). We compiled an index of these numeric ratings called CRI to avoid problems with multicollinearity (the ratings are very similar in most cases). This was a way to handle the multicollinearity problem without losing observations and thus statistical power. By compiling an index we improved the quality of the regression without compromising the quality of the variables in any significant way. The ratings did not differ significantly between issuer or specific rating, and thus there should be no significant distortion from the bundling of the different ratings. Due to the non-linear nature of credit ratings and default rates, we have used the logarithm of the CRI to create a variable called $CRILog$.

Credit ratings provide us with a third party opinion on the quality of the banks' risks. However, they have received a fair amount of criticism regarding the conflicts of interest in credit rating agencies, where the agencies have incentives to give their clients good ratings, and the clients have incentives to purchase only the most favorable ratings (Bolton, Freixas, & Sharpio, 2012). We acknowledge this fact, but leave an exhaustive discussion of this outside the scope of the paper. We feel that credit ratings still are interesting measures to include in our research, especially since they play a large role in determining RWs for the standardized approach. Moreover, we are more interested in the trends of the credit ratings rather than the overall level being too high or low. The conflict of interest among credit rating agencies has existed for quite some time, and should thus not impact the trend of declining or increasing ratings as much as the overall levels.

The variables used as explanatory in our regression are $AIRBCorp$, $FIRBCorp$, $IRBtotal$, $SAtotal$ and $RWtotal$, which are all risk-weights. Risk-Weights (RWs) are defined as the percentage of Risk-Weighted Assets (RWA) in relation to the Exposure at Default (EAD)

$$RW = \frac{RWA}{EAD} = \frac{12.5 * Capital\ Requirements}{EAD} \qquad (4.1.1)$$

The only difference between $AIRBCorp$, $FIRBCorp$, $IRBtotal$ and $SAtotal$ is that they represent different exposures and approaches. $AIRBCorp$ and $FIRBCorp$ are measures for corporate exposure exclusively, and divided into the Foundation approach (FIRB) and Advanced approach (AIRB). We elected to break them out as individual variables since we believe this is where we will find most evidence for RW manipulation, i.e. regulatory arbitrage. $IRBtotal$ and $SAtotal$ are risk weights for the total exposures for the two IRB-approaches and the Standardized approach respectively. $RWtotal$ is the risk-weight for the total exposure regardless of approach (IRB, Standardized) or type of exposure (retail, corporate, sovereign etc.). It is simply the overall average RW for the bank's total exposures.

$NetLOAN$ and $NonPERF$ are accounting measures of risk. They are all presented as a percentage of total loans in order to exclude the effect of size and make them comparable. Net loan loss ($NetLOAN$) is defined as the actual loan loss the bank has incurred during the last year. It is defined as follows

$$NetLOAN = \frac{Net\ Loan\ Losses}{(Total\ Loans\ -\ Interbank\ Loans)} * \ 100 \qquad (4.1.2)$$

Non-performing loans ($NonPERF$) are the loans that the bank acknowledges as being in or near default.

$$NonPERF = \frac{Non\ Performing\ Loans}{Total\ Loans} * 100 \tag{4.1.3}$$

Total assets ($TotASSET$) is a control variable added to see if there are any scale effects affecting the RWs. Additionally we have used reserves for loan losses ($ResLOAN$) for descriptive statistics. We have also included company and country specific IDs to be able to cluster our sample in different ways. We look at three different clusters being

- CENTRAL – including all European banks not in the two other clusters, mostly from central Europe, but also including Great Britain and France
- NORDIC – including all Nordic banks in the sample
- CRISIS – Portugal, Ireland, Italy, Greece and Spain

A full disclosure of the different clusters can be found in (Table 4.1.2).

4.2 Empirical Strategy

The purpose of this thesis is to investigate the relationship between RWs and different proxies for credit risk. We also want to investigate the credibility of the outputs from the more advanced internal models.

We have used a year and firm fixed effects model to assess the net effect of the predictors on the dependent variables. The dependent variables are the market measures for credit quality, $CDSspread$ and $CRILog$ as well as the accounting measures for credit quality, $NetLOAN$ and $NonPERF$. The explanatory variables of interest are the different RWs, $FIRBcorp$, $AIRBcorp$, $IRBtotal$, $SAtotal$ and $RWtotal$. We have also made separate regressions including FIRB and AIRB respectively to not lose too many observations and statistical power, since we often only have observations of one of these variables for each bank and year. The main regressions are defined as follows

$$\begin{aligned} CDSspread_{it} = \beta_0 + \beta_1(F/A)IRBCorp_{it} + \beta_2 IRBtotal_{it} + \beta_3 SAtotal_{it} \\ + \beta_4 RWtotal_{it} + \beta_5 TotASSET_{it} + \alpha_i + u_{it} \end{aligned} \tag{4.2.1}$$

$$\begin{aligned} CRILog_{it} = \beta_0 + \beta_1(F/A)IRBCorp_{it} + \beta_2 IRBtotal_{it} + \beta_3 SAtotal_{it} \\ + \beta_4 RWtotal_{it} + \beta_5 TotASSET_{it} + \alpha_i + u_{it} \end{aligned} \tag{4.2.2}$$

$$NetLOAN_{it} = \beta_0 + \beta_1(F/A)IRBCorp_{it} + \beta_2 IRBtotal_{it} + \beta_3 SAtotal_{it} + \beta_4 RWtotal_{it} + \beta_5 TotASSET_{it} + \alpha_i + u_{it} \tag{4.2.3}$$

$$NonPERF_{it} = \beta_0 + \beta_1(F/A)IRBCorp_{it} + \beta_2 IRBtotal_{it} + \beta_3 SAtotal_{it} + \beta_4 RWtotal_{it} + \beta_5 TotASSET_{it} + \alpha_i + u_{it} \tag{4.2.4}$$

Where β_k is the coefficient of the explanatory variable, i is the entity (bank), t is time, α_i is the unknown intercept for each entity and u_{it} is the error term. The error term is a two-way error component model for disturbances:

$$u_{it} = \mu_i + \lambda_t + v_{it} \tag{4.2.5}$$

Where μ_i is the unobservable individual effect, λ_t is the unobservable time effect and v_{it} is the remainder stochastic disturbance term. Note that μ_i is time-invariant and λ_t is individual-invariant (Baltagi, 2005).

We will also discuss regional differences when it comes to RWs by dividing our sample into clusters (Table 4.1.2). This analysis will focus on descriptive statistics rather than regression models, considering the size of the sample. Further building on our conclusions from the regional differences, we will exclude the CRISIS countries, being Portugal, Ireland, Italy, Greece and Spain, from our regression to test the robustness of the model. By doing this, we exclude the impact that the European Sovereign-debt crisis might have on our sample.

5. Results

Our results are organized in six parts, Descriptive Statistics, Implications of Descriptive Statistics, Regressions, Implications of Regressions, Robustness and Selection Bias. A comprehensive selection of tables and graphs can be found at the end of the thesis in the tables section.

5.1 Descriptive Statistics

The number of observations of the RWs in the dataset varies widely between the different variables due to different approaches applied between banks (Table 5.1.1). Most banks use one of either FIRB and AIRB at the same time, only a few banks utilize both simultaneously. This is not the case when it comes to the Standardized approach which most banks use regardless of their IRB-approach. The years 2007, 2008 and 2014 have the least observations (Tables 5.1.5 through 5.1.12). In 2007 most banks had not yet implemented the RWs, the only ones who had were the Swedish banks and a few German savings banks. These banks' RWs were also lower than average, distorting the trend.

Table 5.1.1 *This table displays the number of observations, mean, standard deviation, minimum and maximum for all the risk-weight variables, market measures of risk, accounting measures of risk and total assets.*

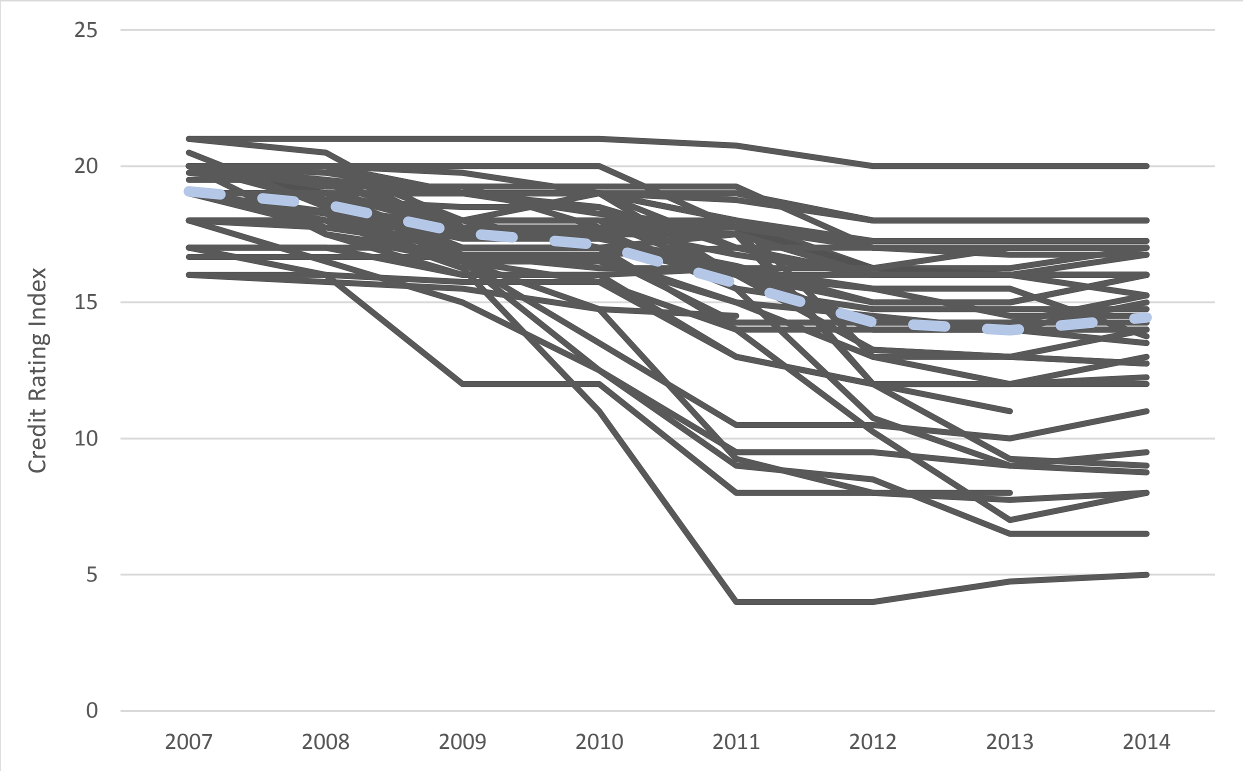
VARIABLES	N	Mean	Sd	Min	Max
FIRBCorp	161	0.652	0.197	0.244	1.560
AIRBCorp	193	0.485	0.143	0.158	0.890
IRBtotal	294	0.343	0.110	0.0585	0.774
Satotal	324	0.430	0.246	0.0275	1.822
Rwtotal	332	0.367	0.136	0.0495	0.875
CDSspread	265	175.1	202.2	3.500	1,905
CRI	397	16.35	3.160	4	21
CRILog	397	2.769	0.248	1.386	3.045
NetLOAN	232	0.343	0.644	-1.400	6.140
NonPERF	249	6.384	14.36	0.0600	130.0
TotASSET	423	526,066	579,020	2,484	3.070e+06

We observe that the means of the RWs are higher in the countries hit hardest by the crisis in 2008 (Portugal, Italy, Ireland, Greece and Spain), (Table 5.1.3) which would be expected given the economic climate in these countries post 2008. We can also see that the means for RWs are lower than average in the Nordic region (Table 5.1.2) where the financial crisis did not impact the economy to the same extent as in the rest of Europe. The distribution of banks between countries (Graph 5.1.7) is as expected affected by the size of the economies but to a larger extent by the number of banks using IRB-methods in each country.

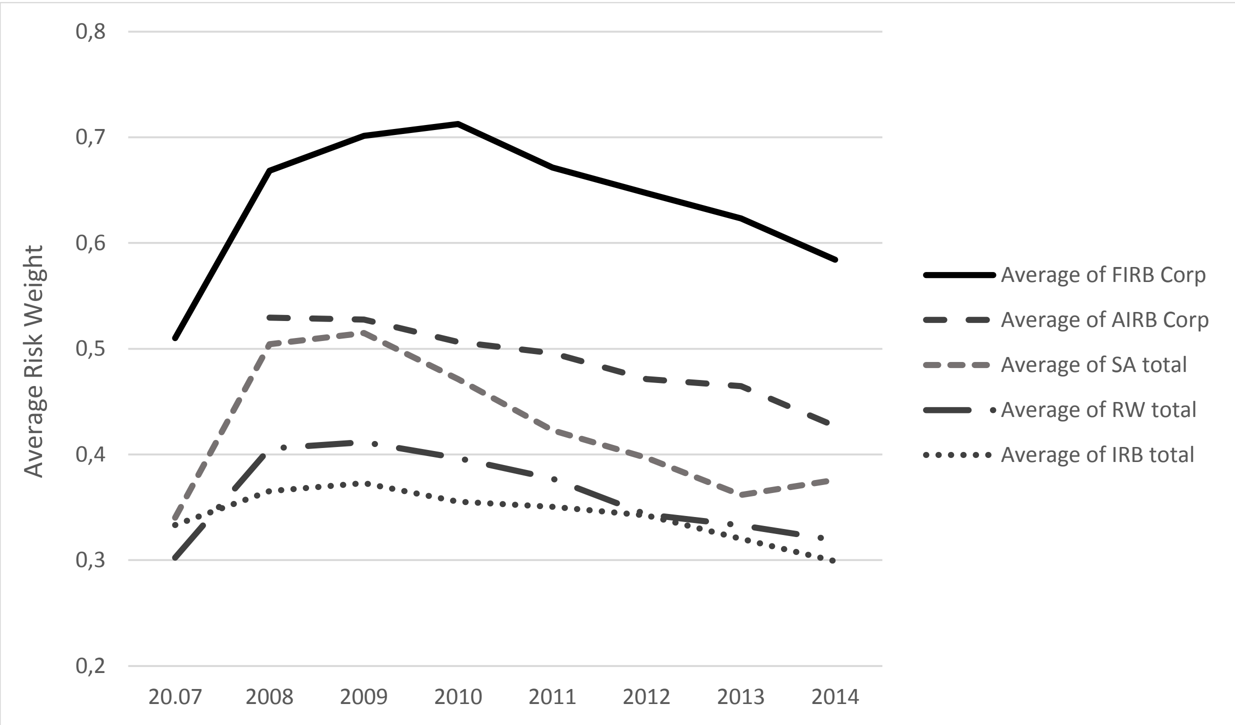
The credit ratings in 2007 are largely the same for all the banks but start to spread out in 2008 and by 2014 the variation is a lot larger as seen below (Graph 5.1.1). The average rating has decreased from 19 (AA, S&P-scale) to 14 (BBB+, S&P-scale) over eight years, a 26% drop. CDS-spreads have increased, with high volatility, under the same period (Graph 5.1.6) indicating that the market also believes that the credit quality has decreased. Non-performing loans and net loan losses have increased as well (Graph 5.1.3 and 5.1.4) which is consistent with lower credit quality and higher default rates. All four of our proxies for credit quality point to a decrease in credit quality.

In the graph on the next page (Graph 5.1.2) we can see the downward sloping trends of the RWs. As stated above, the observations for 2007 are very few which distorts the trend. These observations are also lower than average (Table 5.1.1, 5.1.5 and 5.1.6) which is due to the selection of banks (Swedish banks and German savings banks) for this year. In order to get a correct sense of the trends one should see 2008 as the first year. The RWs in our sample have declined on average by over 21% between 2008 and 2014.

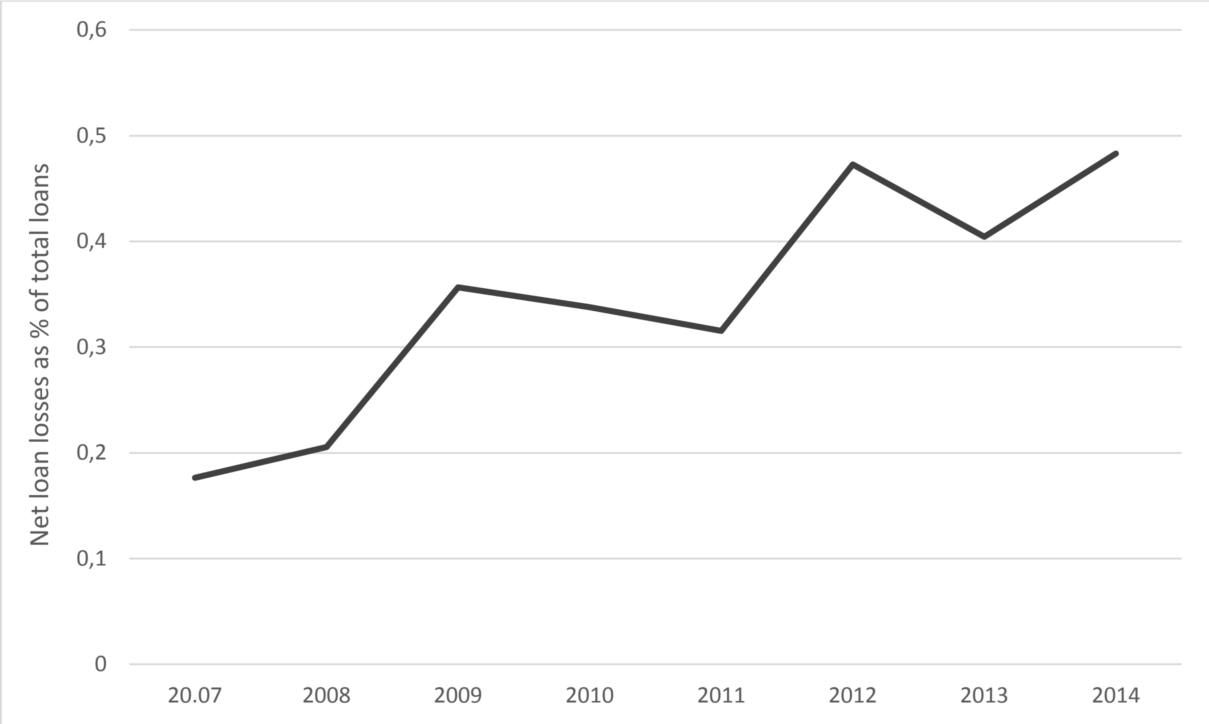
Graph 5.1.1 – Credit Rating Index (CRI) *This graph illustrates the development of the banks' credit ratings. It is our compiled Credit Ratings Index that is displayed. The average is displayed as the dashed light blue line. The other lines are individual banks. The scale we have used goes from 21 (AAA, S&P-scale) to 1 (D, S&P-scale).*



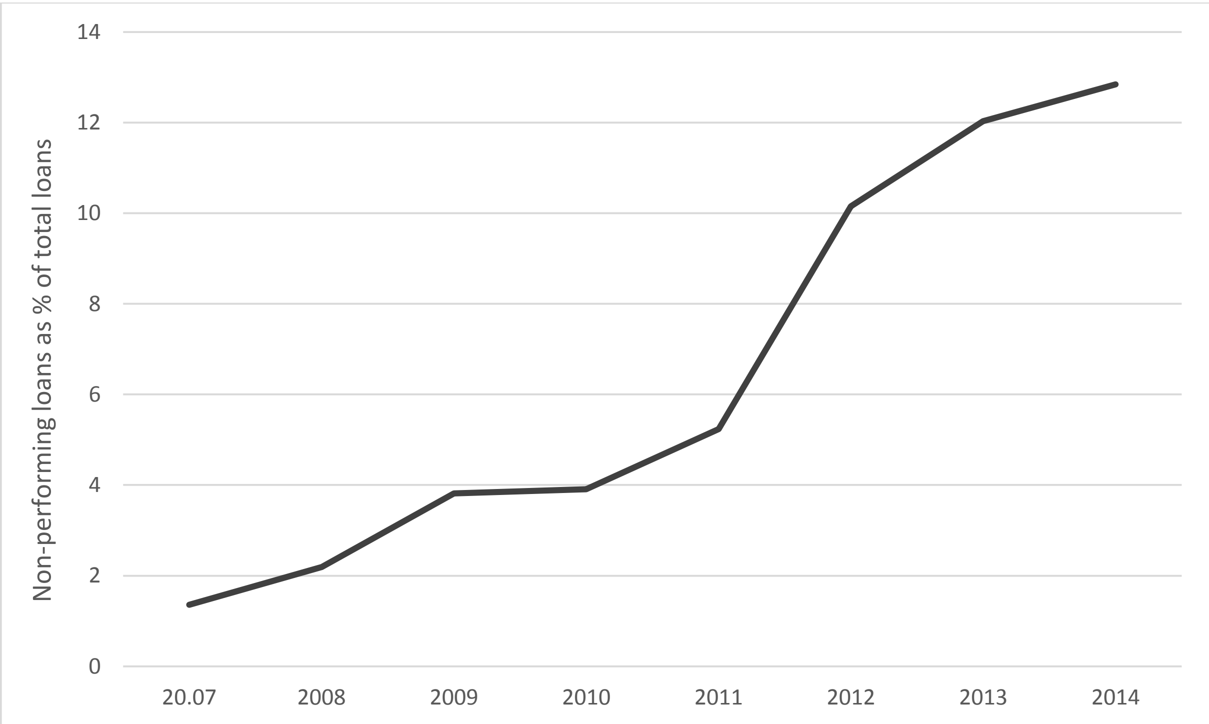
Graph 5.1.2 – Risk-weight development, *this graph displays the development of the different approaches AIRB, FIRB, Standardized as well as the total risk-weights over time.*



Graph 5.1.3 – Net loan losses as a percentage of total loans, *this graph displays the development of the net loan losses over time*



Graph 5.1.4 – Non-performing loans as a percentage of total loans, *this graph displays the development of the level of non-performing loans over time*



5.2 Implications of the Descriptive Statistics

From looking at (Graph 5.1.1) we can clearly see a drop in many banks' credit ratings. There are a few who manage to retain their credit ratings, but on average the credit ratings for our sample decreases five steps over the course of eight years. The average credit rating for 57 of the largest banks in Europe has fallen to a level just three steps above speculative grade. A significant drop which would indicate that the default risk of the banks' exposures has increased. Given the economic climate in Europe post 2008 this comes as no surprise. What we would expect to see if the RWs reflected credit risk properly, is an increase in the RWs during this same period. But while the average ratings have decreased by 26%, the RWs have decreased by 21%. Given that the ratings work as an indicator of credit risk of the banks' exposures, there should have been a corresponding increase in the RWs since these should reflect the increased credit risk of the exposures. Instead we see a steady decline in the level of RWs. This finding supports our first hypothesis that the RWs do not reflect the actual credit risk held by the banks.

The Standardized approach has decreased just as much if not more than the IRB-approaches in our sample. For very secure sovereign exposures the risk weights are zero using the Standardized approach (Table 2.2.1). Therefore there are no reasons to apply the IRB-model to these portfolios. However, for very safe corporate and retail exposures (AAA to AA) the IRB-method can be beneficially applied due to the increasing marginal returns on manipulating RWs for low-risk portfolios as described by Behn et al. (2014), (Figure 2.5.1). The reason why the benefit of the IRB-method differs between exposures is due to the different rules that apply to different types of exposures in the Standardized approach.

Under these prerequisites the banks will start using IRB-models for their riskier portfolios, and the exposures still left under the Standardized approach will be relatively less risky – containing mainly sovereign and other very secure exposures.

Given the trend that banks use the IRB-approach for their riskier exposures the average IRB risk-weight should be higher than for the Standardized approach, assuming the Standardized approach does not overestimate the riskiness of the underlying exposures. This is not the case in our results. When we compare $SAtotal$ with $IRBtotal$ we can see that $IRBtotal$ starts out lower and continues to decrease over time. One possible explanation for the decrease in RWs for IRB-loans would be that the banks initially only shifted their very risky exposures to the IRB-models, and are only gradually shifting over their less risky and extremely secure exposures, thus resulting in lower IRB RWs. This however, does not explain why $IRBtotal$ starts out at much lower RWs in 2008 than $SAtotal$. We can conclude that one of the following must be true: (1) the Standardized approach is systematically overestimating the riskiness of its loans or (2) the IRB approach is systematically underestimating the riskiness of its loans – assuming that one of the models is a more accurate predictor of risk. What is clear from our results is that the IRB-approach allows the banks to report more beneficial levels of RWs.

While the RWs have decreased, the market and accounting measures we have used as proxies for risk all point towards lower credit quality and higher probability of default. The credit ratings' steady decline over the eight years is a sign of increased probability of default and should be a reflection of the banks' exposure. However, rating institutions received a lot of criticism after the crash in 2008. Renowned scholars claimed that the ratings did not reflect actual risk and questioned the independence and integrity of the ratings (Becker & Milbourn, 2011). The decreasing ratings, and more importantly, the increased variance in ratings post 2008 (Graph 5.1.1) can be seen as an attempt to regain the markets' confidence in the ratings, although decreasing ratings are expected following a market crash. Increasing and volatile CDS-spreads are also consistent with higher probability of default. All the market measures of credit quality indicate that the risks held by the banks have increased, rather than decreased which the declining RWs would suggest.

When looking at the accounting measures used as proxies for risk we see that both non-performing loans and net loan losses, as ratios of total loans, increase during these eight years. This is inconsistent with the theory behind RWs. RWs are based on historical accounting measures and performance. An increase in defaults and losses from defaulting loans should cause the RWs to increase. However, our results point in the opposite direction which leads us to conclude that RWs do not properly reflect credit risk.

5.3 Regressions

Our results from the regression of the RWs against different proxies for credit risk support our first hypothesis that RWs do not reflect what the market thinks about the riskiness of the underlying assets. Our primary variable of interest here is the total average RW ($RWtotal$), since our proxies for risk are not exposure specific. $RWtotal$ will tell us how the overall average RWs have developed for the bank as an entity, and thus in theory should capture the entire credit risk that is captured by the the CDS-spread and the credit ratings.

When looking at the results from (table 5.3.1 and 5.3.2), we can see that all the coefficients are positive for $RWtotal$ regressed against the credit rating index ($CRILog$), and highly significant. This result implies that higher RWs are associated with higher credit ratings, and thus that lower RWs are associated with lower credit ratings. This supports our hypothesis that IRB-models do not work as intended, since a working model would have a negative relationship with credit ratings – meaning that lower RWs would reflect higher credit ratings. The same relationship (with positive correlations) is evident in the $FIRBCorp$ and $AIRBCorp$ variables regressed against the rating index, and especially for $FIRBCorp$ where the results are highly significant. The result that is hardest to interpret is that $SAtotal$ has positive coefficients in all cases, which is unintuitive but can largely be explained by the fact that the credit ratings represent not just the Standardized approach exposures but also the IRB-exposures of the firm. This will be discussed more in detail further down.

Table 5.3.1 - Regression, CRILog *as the dependent variable, risk-weights, FIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) CRILog	(2) CRILog	(3) CRILog	(4) CRILog	(5) CRILog
FIRBCorp	0.819***	0.797***	0.379***	0.594***	0.624***
	(0.154)	(0.162)	(0.0927)	(0.160)	(0.170)
IRBtotal		0.0778	0.194	-0.871	-0.789
		(0.337)	(0.341)	(0.589)	(0.632)
SAtotal			0.801***	0.157	0.120
			(0.228)	(0.297)	(0.324)
RWtotal				1.936**	1.937**
				(0.835)	(0.910)
TotASSET					1.11e-07
					(7.01e-08)
Observations	158	150	131	131	128
R-squared	0.270	0.257	0.509	0.577	0.584
Nr of CompanyID-clusters	27	27	25	25	25
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.2 - Regression, CRILog *as dependent variable, risk-weights, AIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) CRILog	(2) CRILog	(3) CRILog	(4) CRILog	(5) CRILog
AIRBCorp	0.797***	0.500	0.501	0.201	0.232
	(0.288)	(0.312)	(0.300)	(0.309)	(0.322)
IRBtotal		0.703*	0.622	0.0974	0.0996
		(0.394)	(0.384)	(0.337)	(0.338)
SAtotal			0.140*	0.0194	0.0293
			(0.0724)	(0.0412)	(0.0423)
RWtotal				1.150***	1.092***
				(0.388)	(0.395)
TotASSET					1.03e-07**
					(4.30e-08)
Observations	175	165	154	154	149
R-squared	0.159	0.198	0.237	0.297	0.306
Nr of CompanyID-clusters	34	33	31	31	30
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.3 - Regression, CDSspread *as dependent variable, risk-weights, FIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) CDSspread	(2) CDSspread	(3) CDSspread	(4) CDSspread	(5) CDSspread
FIRBCorp	-478.5	-415.6	-233.0	-320.0**	-318.9**
	(445.8)	(273.8)	(178.2)	(144.0)	(144.6)
IRBtotal		642.9	1,149	2,259*	2,253*
		(655.1)	(836.5)	(1,151)	(1,171)
SAtotal			-626.8	211.9	213.6
			(389.7)	(555.6)	(555.6)
RWtotal				-2,174*	-2,174*
				(1,092)	(1,099)
TotASSET					-1.51e-05
					(5.57e-05)
Observations	97	90	80	80	80
R-squared	0.034	0.030	0.153	0.233	0.234
Nr of CompanyID-clusters	21	21	20	20	20
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.4 - Regression, CDSspread *as dependent variable, risk-weights, AIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) CDSspread	(2) CDSspread	(3) CDSspread	(4) CDSspread	(5) CDSspread
AIRBCorp	-78.66	70.42	92.01	341.4**	336.0**
	(205.5)	(121.3)	(123.4)	(144.8)	(156.9)
IRBtotal		-187.2	-189.2	167.6	167.0
		(263.1)	(262.9)	(211.1)	(212.8)
SAtotal			-13.13	77.89*	77.01*
			(39.19)	(41.38)	(42.30)
RWtotal				-812.6**	-805.9*
				(392.1)	(407.6)
TotASSET					-9.58e-06
					(5.10e-05)
Observations	145	137	131	131	130
R-squared	0.002	0.008	0.010	0.073	0.073
Nr of CompanyID-clusters	34	33	32	32	31
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The findings from (Tables 5.3.3 and 5.3.4) are also consistent with our main hypothesis. The relationship between $RWtotal$ and the $CDSspread$ is negative – implying that lower RWs are associated with higher risk, which is consistent with our hypothesis that lower RWs do not reflect actual better credit quality. One would expect the opposite relationship in this case.

Presented in table (5.3.5 and 5.3.6), net loan losses ($NetLOAN$) is one of our accounting measures for credit risk, and represents the actual credit losses incurred during a year. In this case, the standard errors for RWtotal are too large to say anything about the relationship for the total risk-weights. In the case of $FIRBCorp$ and $AIRBCorp$ however, we can once more confirm the same finding as those for the market measures. The negative relationship implies that net loan losses increase when the RWs for $AIRBCorp$ and $FIRBCorp$ declines.

The exact same pattern appears in tables (5.3.7 and 5.3.8) when using nonperforming loans ($NonPERF$) as dependent variable. $RWtotal$, $AIRBCorp$, $FIRBCorp$ all have negative coefficients confirming the same conclusion as before. In table (5.3.7) however, we find that $IRBtotal$ has a positive coefficient which is not consistent with our hypothesis.

We also find weak evidence for our second hypothesis that the more advanced the models are, the more the RWs will differ from how the market prices the same risky exposures. All the results point in this direction, but we can not say with confidence that our results from the regression prove anything in this case – mainly due to the fact that our proxies for credit risk are not exposure specific. Another limitation is the potential type II errors inherent in the fact that we do not have a control group. By studying the same banks' reporting according to two different regulations for instance, the magnitude of the manipulation in IRB models could be isolated.

Table 5.3.5 - Regression, NetLOAN *as dependent variable, risk-weights, FIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) NetLOAN	(2) NetLOAN	(3) NetLOAN	(4) NetLOAN	(5) NetLOAN
FIRBCorp	-1.454**	-1.637*	-1.677*	-1.689*	-1.645*
	(0.560)	(0.842)	(0.934)	(0.945)	(0.914)
IRBtotal		0.730	1.378	1.554	1.381
		(1.462)	(1.621)	(1.681)	(1.646)
SAtotal			-0.376	-0.237	-0.251
			(0.336)	(0.713)	(0.731)
RWtotal				-0.384	-0.310
				(1.498)	(1.493)
TotASSET					-2.74e-07
					(2.96e-07)
Observations	93	87	82	82	82
R-squared	0.097	0.096	0.137	0.138	0.147
Nr of CompanyID-clusters	16	16	16	16	16
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.6 - Regression, NetLOAN *as dependent variable, risk-weights, AIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) NetLOAN	(2) NetLOAN	(3) NetLOAN	(4) NetLOAN	(5) NetLOAN
AIRBCorp	-1.037	-1.390*	-1.330*	-1.549*	-1.632*
	(0.729)	(0.754)	(0.735)	(0.815)	(0.822)
IRBtotal		1.314	1.128	0.997	0.880
		(1.279)	(1.315)	(1.306)	(1.187)
SAtotal			-0.0788	-0.123	-0.155
			(0.213)	(0.220)	(0.214)
RWtotal				0.651	0.891
				(1.616)	(1.587)
TotASSET					-3.81e-07*
					(2.07e-07)
Observations	129	126	125	125	125
R-squared	0.033	0.048	0.046	0.048	0.071
Nr of CompanyID-clusters	24	24	24	24	24
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.7 - Regression, NonPERF *as dependent variable, risk-weights, FIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) NonPERF	(2) NonPERF	(3) NonPERF	(4) NonPERF	(5) NonPERF
FIRBCorp	-20.77*	-21.48*	-17.58*	-18.13*	-18.08*
	(11.39)	(11.33)	(9.181)	(10.35)	(10.37)
IRBtotal		-0.557	2.806	30.10**	29.76**
		(6.556)	(7.391)	(12.49)	(13.11)
SAtotal			-10.35*	13.96	13.92
			(5.387)	(10.11)	(10.17)
RWtotal				-62.64**	-62.49**
				(21.81)	(21.95)
TotASSET					-4.38e-07
					(1.21e-06)
Observations	91	86	81	81	81
R-squared	0.149	0.155	0.245	0.388	0.388
Nr of CompanyID-clusters	18	18	18	18	18
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.8 - Regression, NonPERF *as dependent variable, risk-weights, AIRB included as explanatory variables and total assets as control variables*

VARIABLES	(1) NonPERF	(2) NonPERF	(3) NonPERF	(4) NonPERF	(5) NonPERF
AIRBCorp	-12.06**	-6.779*	-6.091*	0.545	0.217
	(4.891)	(3.560)	(3.359)	(4.436)	(4.535)
IRBtotal		-15.28	-16.75	-9.427*	-9.996*
		(10.36)	(10.46)	(5.224)	(4.990)
SAtotal			-1.971	-0.222	-0.393
			(1.513)	(0.645)	(0.678)
RWtotal				-20.11*	-19.27*
				(10.28)	(10.58)
TotASSET					-2.02e-06*
					(1.09e-06)
Observations	130	124	123	123	123
R-squared	0.109	0.160	0.182	0.249	0.265
Nr of CompanyID-clusters	26	25	25	25	25
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.4 Implications of the Regressions

One cautionary note in the interpretation of other variables than $RWtotal$ in our regressions is that our proxies for credit quality concerns the banks' total exposures rather than specifically IRB-exposures or Standardized approach exposures. But one can assume that the credit ratings will be more affected by the IRB-exposures than the Standardized approach exposures, since the risky assets generally reside in the IRB-portfolios. The incentives to shift riskier portfolios to the IRB-model and keep the SA-model for extremely safe sovereign exposures has been explained in this thesis as well as by Behn et al. (2014).

We also have to consider the fact that many renowned scholars such as Becker and Milbourn (2009), Hau et al. (2012) and Bolton et al. (2012) have questioned the ability of credit ratings to predict default rates. Becker and Milbourn conclude that when competition in the rating industry increases, the correlation between market yields and the credit ratings falls. This is of course a real concern, but something we will not discuss in any greater detail. This is due to the fact that we have also included CDS-spreads as market measures of risk, giving us a less subjective view on credit risk. We can however confirm that there a robust relationship between credit ratings and CDS-spreads in our sample. The relationship is very strong when they are regressed individually without control variables, and also when including control variables (Table 5.4.1).

Something else to consider when interpreting the results from the regressions is that RWs are often described as long term measures of risk based on things such as historical loss rates, while accounting measures such as net loan losses and nonperforming loans are better proxies for short term credit risk. Comparing the two is naturally not a straightforward task. This also highlights one of the main problems with RWs as a measure of risk. Since they are based on historical trends they are by definition a backward-looking measure. They will never be able to predict future risk or potential “Black Swans” in a reliable manner. The inherent problem with RWs as measures of future risk are that they seem to lack the predictive abilities they are attributed, since they are based on accounting data and can be updated *ex-post*. This is a key point that is stressed by many scholars such as Hellwig (2010) Arachaya et al. (2014). This is also consistent with the fact that they seem to be able to work better in good times than bad, implying their lack of helpfulness when they are needed the most. These conclusions are supported by our findings. We also hope to add something new to the field by including market measures of risk in our study, since most recent papers in the field such as Behn et al. (2014) and Mariathasan and Merrouche (2012) use only accounting measures in their studies.

5.5 Robustness of the Model

To check the robustness of our model we have included a control variable for total assets, since size effects are the most obvious factors that could explain differences between banks when it comes to their risk taking and to what degree they engage in regulatory arbitrage. More advanced models and lower capital charges are generally associated with larger banks. The results stay intact even including this variable (Tables 5.3.1 - 5.3.8). We have also used the robust option in Stata to control for heteroskedasticity.

We have also dropped the European sovereign-debt crisis countries including Portugal, Italy, Greece, Spain and Ireland to check the robustness of our model. This is due to the arguments made by Mariathasan and Merrouche (2012) that weakly capitalized banks seem to engage in RW manipulation the most. Assuming that RW manipulation is a widespread phenomenon, our results should stay intact even when excluding these crisis countries. The results for $CRILog$ stay largely the same, even though we lose some significance due to fewer observations (5.3.9 and 5.3.10). All coefficients are still pointing in the same direction, supporting our hypothesis. The findings for $CDSspread$ are also intact when it comes to direction on coefficients, even though the results lose most of their significance (Tables 5.3.11 and 5.3.12). The coefficients for $NonPERF$ also stay the same, but lose almost all of their significance (Tables 5.3.13 and 5.3.14). The same applies for $NetLOAN$ (5.3.15 and 5.3.16).

5.6 Possible Selection Biases

When considering possible selection biases in our dataset, the most obvious objection would be that we have chosen banks primarily based on size, and that we would expect a more prominent effect of RW manipulation among the large banks as compared to all banks including the smaller ones. This is of course true, but not a very big concern for us, since our hypothesis implicitly focuses on the larger banks that have adapted, or might in the near future adapt some kind of IRB-model.

Another risk is the inherent possibility of sample selection bias in the secondary sources (Datastream, Bloomberg and Mint) we have used. There are sometimes missing values, and it is often hard to pinpoint errors when using secondary sources.

Another anomaly that is quite prominent in our descriptive statistics is the inclusion of data from 2007, even though Basel II was adapted on a large scale only in early 2008. There are consequently very few observations from 2007, and these are mostly Swedish banks and

German savings banks that generally have much lower RWs than average - making the average RW in 2007 extremely low when compared to the other years (Tables 5.1.1 and 5.1.5). But we elected to keep the observations since we needed all the observations we could get, and have included year and firm fixed effects in the regression.

A last note of caution regarding the data is the relatively large number of German banks included in the sample. A few of these are cooperative savings banks, having exposures that are much less risky than the average European bank – primarily sovereign exposures. We are aware of the fact that this could lower our average RWs in all categories somewhat, especially in the Standardized approach category where the extremely safe German sovereign exposure reside. This is however not a great concern since there are only four such banks in the sample.

6. Conclusion

The idea behind the Basel II Accord was to increase the strength of the financial system and make the banks more solvent. Instead the risk-weights, along with the capital requirements, have decreased substantially since 2008. At the same time, credit ratings have plummeted. In our sample, the risk weights have decreased with 21% and credit ratings have decreased with 26% - confirming our first hypothesis that the diminishing risk-weights do not correspond to a general increase in credit quality.

We have concluded that the IRB-portfolios are generally riskier than SA-portfolios, something that is not reflected in the risk-weights. Risk-weights are consistently lower for IRB-portfolios than for SA-portfolios in our sample – implying either that; (1) the SA-model is overestimating risk, or that (2) the IRB-model is underestimating risk. This supports our second hypothesis that IRB-models are producing artificially low risk-weights, but this is not strong evidence.

Our regressions also confirm a positive relationship between the risk-weights for the total exposures and our credit rating index, and a negative relationship between total exposure risk-weights and CDS-spreads. These results provide further support to our first hypothesis. The results of the regression between our risk-weights and our accounting measures for credit risk also confirm the same relationship, but not with significant results.

In conclusion, we find strong evidence for our first hypothesis that the diminishing risk-weights do not correspond to an increase in credit quality among the banks in our sample. We find weak evidence regarding our second hypothesis that more advanced models provide less accurate risk estimates.

7. Limitations and Suggestions for Future Research

7.1 Limitations

The limitations of our study primarily include sample size, data quality and the lack of a control group to provide causal evidence that the banks are gaming the regulation.

The sample size limits the strength of the statistical tests and a larger sample and longer time series would have improved the statistical strength of the results. However we are limited to the length of the time-series due to Basel II being implemented in 2008. As for the smaller banks we were limited by unsatisfactory reporting in their pillar 3 reports, and sometimes by the lack of public disclosure reports.

We chose not to expand beyond Europe since Basel II was implemented in a different manner in the US. This left us with only the European banks, primarily in the EMU-region. The implication of this is that we can not necessarily extrapolate our findings to other regions that have implemented the Basel II Accord such as the US. But recent empirical evidence by and Becker and Opp (2013) suggest that risk-weight manipulation is prevalent also in the US.

7.2 Suggestions for Future Research

For future research we suggest that scholars within the field look into the implications of returning to more standardized approaches of calculating credit risk. The Basel IV Accord is in the works, proposing a return to less advanced approaches, making it an important issue for future studies to understand how this will affect the banks. We also suggest looking in to possible solutions to the issue with undercapitalized banks, such as a leverage ratio restriction as proposed by Blum (2008), reducing the banks' ability to understate their risk, or increased securitisation as proposed by Wehninger (2012).

References

Acharaya, V., Engle, R., & Pierret, D. (2014). Testing macroprudential stress tests: The risk of regulatory risk weights. *Journal of Monetary Economics 65* , 36-53.

Amati, A. R., DeMarzo, P. M., Hellwig, M. F., & Pfleiderer, P. (2013). Fallacies, Irrelevant Facts, and Myths in the Siscussion of Capital Regulation: Why Bank Equity is Not Socially Expensive. *Preprints of the Max Planck Institute for Research on Collective Goods No 2013/23*.

Baltagi, B. H. (2005). *Econometric Analysis of Panel Data, 3rd Edition.* John Wiley & Sons Ltd.

Basel Committee on Banking Supervision. (1988). *International Convergence of Capital Measurement and Capital Standards.* Bank of International Settlements.

Basel Committee on Banking Supervision. (2004). *Implementation of Basel II: Practical Considerations.* Basel, Switzerland: Bank of International Settlements.

Basel Committee on Banking Supervision. (2004). *International Convergence of Capital Measurements and Capital Standards.* Bank of International Settlements.

Basel Committee on Banking Supervision. (2005). *An Explanatory Note on the Basel II IRB Risk Weight Functions.* Bank of International Settlements.

Basel Committee on Banking Supervision. (2006). *International Convergence of Capital Measurement and Capital Standards, Comprehensive Revised Version.* Bank of International Settlements.

Basel Committee on Banking Supervision. (2013). *Regulatory Consistency Assessment Programme (RCAP): Analysis of risk-weighted assets for credit risk in the banking book.* International Bank of Settlements.

Becker, B., & Milbourn, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics 101(3)*, 493-514.

Becker, B., & Opp, M. (2013). Regulatory reform and risk-taking: Replacing ratings. *NBER Working Paper No. 19257*.

Behn, H. V. (2014). The Limits of Model-Based Regulation. *SAFE Working Paper No. 75, Goethe University Frankfurt*.

Blum, J. M. (2008). Why Basel II may need a leverage ratio restriction. *Journal of Banking and Finance 32*, 1699-1707.

Bolton, P., Freixas, X., & Sharpio, J. (2012). The Credit Rating Game. *The Journal of Finance*, 85-111.

European Banking Authority. (2013a). *First Interim Report on the consistency of risk-weighted assets.*

European Banking Authority. (2013b). *Second Interim Report on the consistency of risk-weighted assets.*

European Banking Authority. (2013c). *Third interim report on the consistency of risk-weighted assets.*

European Banking Authority. (2014). *Fourth Interim Report on the consistency of risk-weighted assets.*

Glaeser, E. L., & Schleifer, A. (2001). A Reason for Quantity Regulation. *The American Economic Review*, 431-435.

Hasan, I., & Zazzara, C. (2006). Pricing risky bank loans in the new Basel II environment . *Discussion Papers 3, Bank of Finland Research*.

Hau, H., Langfield, S., & Marques-Ibanez, D. (2013). Bank ratings: What determines their quality? *Economic Policy 28 (74)*, 289-333.

Hellwig, M. F. (2010). Capital Regulation after the Crisis: Business as Usual? *MPI Collective Goods Preprint, No. 2010/31*.

KPMG. (2013). *Basel 4 – Emerging from the mist?*

Le Leslé , V., & Avramova, S. (2012). Revisiting Risk-Weighted Assets: "Why Do RWA Differ Across Countries and What Can Be Done About It?". *IMF Working Paper*.

Lind, G. (2005). Basel II - nytt regelverk för bankkapital. *Penning- och valutapolitik*.

Mariathasan, M., & Merrouche, Q. (2014). The Manipulation of Basel Risk-Weights. *Journal of Financial Intermediation 23 (3)*, 300-321.

Wehninger, G. (2012). Bank deleveraging, the move from bank to market-based financing. *OECD Journal 2012/1*.

Wooldridge, J. M. (2012). *Introductory Econometics, 5th Edition.* South-Western.

Tables, Graphs and Figures

Tables

Table 3.1.1 - Banks used in the dataset

RAIFFEISEN ZENTRALBANK ÖSTERREICH (RZB)	AT
BELFIUS (DEXIA)	BE
KBC BANK	BE
ARGENTA	BE
CREDIT SUISSE	CH
UBS AG	CH
DEUTSCHE BANK AG	DE
COMMERZBANK AG	DE
DZ BANK	DE
LANDESBANK BADEN-WÜRTTEMBERG (LBBW)	DE
NORDDEUTSCHE LANDESBANK (NORD/LB)	DE
PORTIGON FINANCIAL SERVICES	DE
BAYERISCHE LANDESBANK (BAYERN LB)	DE
LANDESBANK HESSEN-THÜRINGEN GIROZENTRALE (HELABA)	DE
DEKA GROUP	DE
DANSKE BANK	DK
SYDBANK	DK
NYKREDIT	DK
FIH EHRVERVSBANK	DK
SPAR NORD BANK	DK
ALM BRAND BANK	DK
VESTJYSK BANK	DK
BANCO SANTANDER S.A.	ES
BANCO BILBAO VIZCAYA ARGENTARIA S.A. (BBVA)	ES
BANCO SABADELL	ES
CAIXA BANK	ES
BANCO POPULAR ESPANOL	ES
BNP PARIBAS	FR
GROUPE CREDIT AGRICOLE	FR
SOCIETE GENERALE	FR
GROUPE BPCE	FR
BANQUE FÉDÉRATIVE CREDIT MUTUEL (BFCM)	FR
ROYAL BANK OF SCOTLAND GROUP PLC	GB
HSBC HOLDINGS PLC	GB
BARCLAYS PLC	GB
LLOYDS BANKING GROUP PLC	GB
NATIONWIDE BUILDING SOCIETY	GB
NATIONAL BANK OF GREECE	GR

ALLIED IRISH BANKS PLC IE	IE
IRISH LIFE AND PERMANENT	IE
BANK OF IRELAND	IE
INTESA SANPAOLO S.P.A	IT
UNICREDIT S.P.A	IT
BANCA MONTE DEI PASCHI DI SIENA S.P.A	IT
BANCO POPOLARE - S.C.	IT
UNIONE DI BANCHE ITALIANE SCPA (UBI BANCA)	IT
BANQUE ET CAISSE D’EPARGNE DE L’ETAT, LUXEMBOURG	LU
BANQUE INTERNATIONALE À LUXEMBOURG	LU
DEN NORSKE BANK (DNB)	NO
ING BANK NV	NL
RABOBANK NEDERLAND	NL
ABN AMRO	NL
BANCO COMERCIAL PORTUGUÊS, SA (BCP OR MILLENNIUM BCP)	PT
NORDEA BANK AB	SE
SKANDINAVISKA ENSKILDA BANKEN AB (SEB)	SE
SVENSKA HANDELSBANKEN AB	SE
SWEDBANK AB	SE

Table 3.1.2 -List of variables in dataset

Variable	**Source**	**Description**
FIRB Corp	Pillar 3 report	RW, Corporate, Foundation approach IRB
AIRB Corp	Pillar 3 report	RW, Corporate, Advanced approach IRB
IRB total	Pillar 3 report	RW, Total, Foundation approach IRB
SA total	Pillar 3 report	RW, Total, Standardized approach IRB
RWtotal	Pillar 3 report	RW, Total, Foundation+Standardized approach IRB
SA EAD	Pillar 3 report	Standardized approach, Exposure at Default
FIRB EAD	Pillar 3 report	Foundation IRB approach, Exposure at Default
AIRB EAD	Pillar 3 report	Advanced IRB approach, Exposure at Default
Total IRB EAD	Pillar 3 report	Total IRB, Exposure at Default
Total EAD	Pillar 3 report	Total, Exposure at Default
SA Ratio	Pillar 3 report	SA EAD / Total EAD
FIRB Ratio	Pillar 3 report	FIRB EAD / Total EAD
AIRB Ratio	Pillar 3 report	AIRB EAD / Total EAD
Total IRB Ratio	Pillar 3 report	Total IRB EAD / Total EAD
CRI	Bloomberg	Credit Rating Index
CRILog	Bloomberg	Logarithm of CRI
CDSspread	Datastream	Spread between CDS and suitable benchmark
NetLOAN	Datastream/Mint	Net loan losses as a percentage of total loans
NonPERF	Datastream	Non-performing loans as a percentage of total loans
ResLOAN	Datastream	Reserves for loan losses as a percentage of total loans
TotASSET	Datastream/Mint	Total assets, from balance sheet, in MEUR

Table 4.1.1 - Rating Cross-table

Moody's	S&P	Numeric	
Aaa	AAA	21	Investment Grade
Aa1	AA+	20	
Aa2	AA	19	
Aa3	AA-	18	
A1	A+	17	
A2	A	16	
A3	A-	15	
Baa1	BBB+	14	
Baa2	BBB	13	
Baa3	BBB-	12	
Ba1	BB+	11	Speculative Grade
Ba2	BB	10	
Ba3	BB-	9	
B1	B+	8	
B2	B	7	
B3	B-	6	
Caa1	CCC+	5	
Caa2	CCC	4	
Caa3	CCC-	3	
Ca	CC and C	2	
C	SD and D	1	

Table 4.1.2 - Regional Clusters

CENTRAL	NORDIC
Germany (DE)	Sweden (SE)
Austria (AT)	Denmark (DK)
Belgium (BE)	Norway (NO)
Schweiz (CH)	
France (FR)	**CRISIS**
Luxembourg (LU)	Spain (ES)
Netherlands (NL)	Italy (IT)
Great Britain (GB)	Portugal (PT)
	Greece (GR)
	Ireland (IE)

Table 5.1.2 - Descriptive statistics, *Nordic region only.*

VARIABLES	N	mean	sd	min	max
FIRBCorp	28	0.548	0.113	0.328	0.771
AIRBCorp	37	0.431	0.130	0.229	0.701
IRBtotal	53	0.325	0.0998	0.171	0.532
SAtotal	70	0.388	0.208	0.0784	0.875
RWtotal	72	0.411	0.160	0.150	0.875
CDSspread	40	122.4	98.92	4.100	422.9
CRI	78	16.60	2.699	8	20
CRILog	78	2.793	0.194	2.079	2.996
NetLOAN	62	0.248	0.358	-0.610	1.980
NonPERF	58	1.476	1.801	0.0600	8.820
TotASSET	88	196,392	190,708	2,484	709,169

Table 5.1.3 - Descriptive statistics, *CRISIS-region (Portugal, Italy, Ireland, Greece and Spain) only*

VARIABLES	N	mean	sd	min	max
FIRBCorp	42	0.844	0.214	0.520	1.560
AIRBCorp	48	0.564	0.0967	0.400	0.809
IRBtotal	68	0.424	0.115	0.212	0.774
SAtotal	84	0.475	0.162	0.0275	0.910
RWtotal	84	0.438	0.106	0.230	0.764
CDSspread	91	277.8	301.5	7.900	1,905
CRI	112	14.20	4.209	4	20
CRILog	112	2.598	0.361	1.386	2.996
NetLOAN	61	0.414	1.004	-1.400	6.140
NonPERF	79	9.975	8.436	0.500	36.71
TotASSET	120	312,966	330,588	35,904	1.250e+06

Table 5.1.4 - Descriptive statistics, *excluding CRISIS-region (Portugal, Italy, Ireland, Greece and Spain)*

VARIABLES	N	mean	sd	min	max
FIRBCorp	119	0.584	0.138	0.244	1.039
AIRBCorp	145	0.459	0.146	0.158	0.890
IRBtotal	226	0.319	0.0967	0.0585	0.532
SAtotal	240	0.415	0.268	0.0323	1.822
RWtotal	248	0.343	0.137	0.0495	0.875
CDSspread	174	121.4	81.75	3.500	452.3
CRI	285	17.20	2.113	8	21
CRILog	285	2.836	0.137	2.079	3.045
NetLOAN	171	0.317	0.452	-0.610	2.700
NonPERF	170	4.715	16.16	0.0600	130.0
TotASSET	303	610,462	632,636	2,484	3.070e+06

Table 5.1.5 - Descriptive statistics, *for risk-weights per year 2007*

VARIABLES	N	mean	sd	min	max
FIRBCorp	8	0.510	0.127	0.304	0.725
IRBtotal	8	0.333	0.0940	0.242	0.480
SAtotal	6	0.340	0.138	0.135	0.478
RWtotal	7	0.302	0.0654	0.183	0.366

Table 5.1.6 - Descriptive statistics, *for risk-weights per year 2008*

VARIABLES	N	mean	sd	min	max
FIRBCorp	18	0.668	0.251	0.423	1.560
AIRBCorp	17	0.529	0.164	0.277	0.840
IRBtotal	31	0.365	0.118	0.124	0.738
SAtotal	32	0.504	0.265	0.116	1.448
RWtotal	32	0.406	0.145	0.124	0.874

Table 5.1.7 - Descriptive statistics, *for risk-weights per year 2009*

VARIABLES	N	mean	sd	min	max
FIRBCorp	22	0.701	0.199	0.430	1.240
AIRBCorp	23	0.527	0.142	0.265	0.850
IRBtotal	42	0.373	0.124	0.0880	0.774
SAtotal	46	0.515	0.294	0.0800	1.822
RWtotal	47	0.412	0.149	0.122	0.833

Table 5.1.8 - Descriptive statistics, *for risk-weights per year 2010*

VARIABLES	N	mean	sd	min	max
FIRBCorp	22	0.712	0.224	0.457	1.340
AIRBCorp	29	0.506	0.153	0.181	0.850
IRBtotal	43	0.355	0.106	0.0955	0.637
SAtotal	49	0.471	0.264	0.0796	1.632
RWtotal	50	0.397	0.141	0.112	0.808

Table 5.1.9 - Descriptive statistics, *for risk-weights per year 2011*

VARIABLES	N	mean	sd	min	max
FIRBCorp	22	0.671	0.180	0.436	1.150
AIRBCorp	31	0.496	0.151	0.158	0.810
IRBtotal	46	0.351	0.109	0.114	0.652
SAtotal	50	0.423	0.201	0.0784	0.800
RWtotal	51	0.377	0.127	0.120	0.800

Table 5.1.10 - Descriptive statistics, *for risk-weights per year 2012*

VARIABLES	N	mean	sd	min	max
FIRBCorp	26	0.647	0.185	0.244	1.026
AIRBCorp	33	0.471	0.148	0.164	0.840
IRBtotal	38	0.342	0.123	0.0585	0.664
SAtotal	53	0.397	0.213	0.0465	0.847
RWtotal	55	0.343	0.137	0.100	0.775

Table 5.1.11 - Descriptive statistics, *for risk-weights per year 2013*

VARIABLES	N	mean	sd	min	max
FIRBCorp	26	0.623	0.175	0.274	0.960
AIRBCorp	33	0.465	0.135	0.187	0.890
IRBtotal	51	0.320	0.100	0.124	0.532
SAtotal	53	0.362	0.214	0.0323	0.875
RWtotal	54	0.333	0.131	0.0495	0.875

Table 5.1.12 - Descriptive statistics, *for risk-weights per year 2014*

VARIABLES	N	mean	sd	min	max
FIRBCorp	17	0.584	0.166	0.328	0.867
AIRBCorp	27	0.427	0.0900	0.229	0.594
IRBtotal	35	0.299	0.0839	0.170	0.484
SAtotal	35	0.376	0.262	0.0275	1.387
RWtotal	36	0.319	0.104	0.150	0.622

Table 5.3.9 - Regression CRILog, *excluding Portugal, Italy, Ireland, Greece and Spain, CRILog as dependent variable, risk-weights, FIRB included as explanatory variables and total assets as control variable*

	(1)	(2)	(3)	(4)	(5)
VARIABLES	CRILog	CRILog	CRILog	CRILog	CRILog
FIRBCorp	0.141	0.0865	0.0756	0.0570	0.0957
	(0.0987)	(0.119)	(0.123)	(0.109)	(0.108)
IRBtotal		0.168	-0.0318	-0.526	-0.321
		(0.228)	(0.218)	(0.353)	(0.341)
SAtotal			0.380***	0.0900	0.0725
			(0.114)	(0.158)	(0.172)
RWtotal				1.047**	0.907*
				(0.451)	(0.432)
TotASSET					1.20e-07***
					(3.90e-08)
Observations	116	112	93	93	90
R-squared	0.023	0.029	0.288	0.346	0.378
Nr of CompanyID-clusters	18	18	16	16	16
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.10 - Regression CRILog, *excluding Portugal, Italy, Ireland, Greece and Spain, CRILog as dependent variable, risk-weights, AIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) CRILog	(2) CRILog	(3) CRILog	(4) CRILog	(5) CRILog
AIRBCorp	0.389***	0.292**	0.296**	0.0178	0.0660
	(0.0967)	(0.124)	(0.108)	(0.164)	(0.156)
IRBtotal		0.229	0.152	-0.214	-0.203
		(0.182)	(0.135)	(0.233)	(0.215)
SAtotal			0.114***	0.0257	0.0424**
			(0.0343)	(0.0194)	(0.0199)
RWtotal				0.930**	0.804**
				(0.333)	(0.315)
TotASSET					1.27e-07***
					(3.97e-08)
Observations	133	129	118	118	113
R-squared	0.095	0.105	0.195	0.303	0.362
Nr of CompanyID-clusters	25	25	23	23	22
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.11 – Regression CDSspread, *excluding Portugal, Italy, Ireland, Greece and Spain, CDSspread as dependent variable, risk-weights, FIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) CDSspread	(2) CDSspread	(3) CDSspread	(4) CDSspread	(5) CDSspread
FIRBCorp	-104.5	-68.89	-252.5	-258.9	-261.7
	(153.8)	(201.2)	(186.8)	(166.4)	(176.6)
IRBtotal		125.7	239.6	895.4*	691.2
		(222.9)	(257.9)	(407.4)	(527.6)
SAtotal			140.2	325.1***	313.5***
			(83.44)	(75.57)	(86.43)
RWtotal				-853.4**	-689.6
				(308.7)	(410.5)
TotASSET					-7.38e-05*
					(3.68e-05)
Observations	66	62	52	52	52
R-squared	0.014	0.012	0.125	0.175	0.209
Nr of CompanyID-clusters	13	13	12	12	12
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.12 – Regression CDSspread, *excluding Portugal, Italy, Ireland, Greece and Spain, CDSspread as dependent variable, risk-weights, AIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) CDSspread	(2) CDSspread	(3) CDSspread	(4) CDSspread	(5) CDSspread
AIRBCorp	123.0	82.36	131.0	161.1	99.10
	(108.8)	(79.13)	(89.08)	(122.2)	(144.8)
IRBtotal		146.7*	134.7	161.6**	151.1*
		(72.24)	(85.37)	(71.52)	(85.68)
SAtotal			7.064	13.99	6.889
			(16.56)	(27.55)	(26.80)
RWtotal				-71.68	-2.077
				(156.6)	(162.1)
TotASSET					-5.58e-05
					(4.05e-05)
Observations	102	100	94	94	93
R-squared	0.008	0.024	0.032	0.033	0.052
Nr of CompanyID-clusters	24	24	23	23	22
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.13 – Regression NonPERF, *excluding Portugal, Italy, Ireland, Greece and Spain, NonPERF as dependent variable, risk-weights, FIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) NonPERF	(2) NonPERF	(3) NonPERF	(4) NonPERF	(5) NonPERF
FIRBCorp	-4.896	-5.684	-7.055	-6.816	-6.810
	(4.302)	(4.243)	(4.219)	(3.897)	(3.999)
IRBtotal		3.609	2.373	9.702	8.856
		(2.417)	(2.245)	(8.832)	(9.423)
SAtotal			0.457	3.706	3.578
			(1.510)	(2.977)	(3.088)
RWtotal				-12.50	-11.77
				(12.15)	(12.76)
TotASSET					-4.84e-07
					(3.57e-07)
Observations	65	61	56	56	56
R-squared	0.084	0.108	0.154	0.188	0.191
Nr of CompanyID-clusters	11	11	11	11	11
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.14 – Regression NonPERF, *excluding Portugal, Italy, Ireland, Greece and Spain, NonPERF as dependent variable, risk-weights, AIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) NonPERF	(2) NonPERF	(3) NonPERF	(4) NonPERF	(5) NonPERF
AIRBCorp	-4.510	-5.347*	-5.313*	-7.191	-8.285**
	(2.625)	(2.792)	(2.728)	(4.396)	(3.931)
IRBtotal		3.391	3.374	2.616	1.866
		(3.151)	(3.267)	(1.986)	(1.654)
SAtotal			0.289	0.0197	-0.241
			(0.428)	(0.530)	(0.579)
RWtotal				4.973	7.374
				(8.855)	(8.721)
TotASSET					-2.64e-06**
					(1.00e-06)
Observations	95	93	92	92	92
R-squared	0.042	0.051	0.050	0.058	0.157
Nr of CompanyID-clusters	19	19	19	19	19
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.15 – Regression NetLOAN, *excluding Portugal, Italy, Ireland, Greece and Spain, NetLOAN as dependent variable, risk-weights, FIRB included as explanatory variables and total assets as control variable*

VARIABLES	(1) NetLOAN	(2) NetLOAN	(3) NetLOAN	(4) NetLOAN	(5) NetLOAN
FIRBCorp	-1.381**	-1.421	-1.910	-1.917	-1.895
	(0.535)	(0.845)	(1.078)	(1.081)	(1.051)
IRBtotal		1.011	1.549	2.266	1.860
		(1.636)	(1.732)	(3.248)	(3.190)
SAtotal			0.249	0.517	0.469
			(0.180)	(0.887)	(0.895)
RWtotal				-1.115	-0.773
				(3.735)	(3.748)
TotASSET					-1.83e-07
					(2.65e-07)
Observations	64	60	55	55	55
R-squared	0.092	0.092	0.154	0.158	0.165
Nr of CompanyID-clusters	10	10	10	10	10
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.16 – Regression NetLOAN, *excluding Portugal, Italy, Ireland, Greece and Spain, NetLOAN as dependent variable, risk-weights, AIRB included as explanatory variables and total assets as control variables*

VARIABLES	(1) NetLOAN	(2) NetLOAN	(3) NetLOAN	(4) NetLOAN	(5) NetLOAN
AIRBCorp	-0.293	-0.652	-0.604	-0.902	-1.034
	(0.884)	(0.828)	(0.802)	(0.860)	(0.844)
IRBtotal		1.388	1.226	1.098	0.994
		(1.360)	(1.410)	(1.325)	(1.204)
SAtotal			-0.0248	-0.0773	-0.111
			(0.206)	(0.210)	(0.205)
RWtotal				0.848	1.190
				(1.499)	(1.464)
TotASSET					-3.86e-07*
					(2.17e-07)
Observations	106	104	103	103	103
R-squared	0.003	0.023	0.019	0.023	0.054
Nr of CompanyID-clusters	20	20	20	20	20
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.17 - Regression RWtotal, *full sample, with RWtotal as dependent the other risk-weights as explanatory variables and total assets as control variable*

VARIABLES	(1) RWtotal	(2) RWtotal	(3) RWtotal
TotASSET	1.30e-08	2.85e-08***	2.25e-08***
	(1.05e-08)	(8.25e-09)	(5.64e-09)
SAtotal	0.343***	0.105***	0.221***
	(0.0677)	(0.0343)	(0.0355)
IRBtotal	0.551***	0.459**	0.646***
	(0.0724)	(0.208)	(0.0668)
FIRBCorp	-0.121**		-0.0738
	(0.0527)		(0.0642)
AIRBCorp		0.264**	0.189**
		(0.105)	(0.0786)
Observations	131	166	42
R-squared	0.782	0.699	0.909
Nr of CompanyID-clusters	27	33	10
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3.18 - Regression, *excluding Portugal, Italy, Ireland, Greece and Spain, with RWtotal as dependent, risk-weights as explanatory variables and total assets as control variable*

VARIABLES	(1) RWtotal	(2) RWtotal	(3) RWtotal
TotASSET	1.44e-08	3.32e-08***	2.76e-08***
	(8.64e-09)	(8.40e-09)	(1.59e-09)
SAtotal	0.283***	0.0954***	0.229***
	(0.0248)	(0.0268)	(0.0100)
IRBtotal	0.483***	0.386	0.633***
	(0.111)	(0.229)	(0.0506)
FIRBCorp	0.0109		-0.0409
	(0.0434)		(0.0572)
AIRBCorp		0.303**	0.326*
		(0.128)	(0.155)
Observations	93	124	29
R-squared	0.858	0.683	0.911
Nr of CompanyID-clusters	18	24	7
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

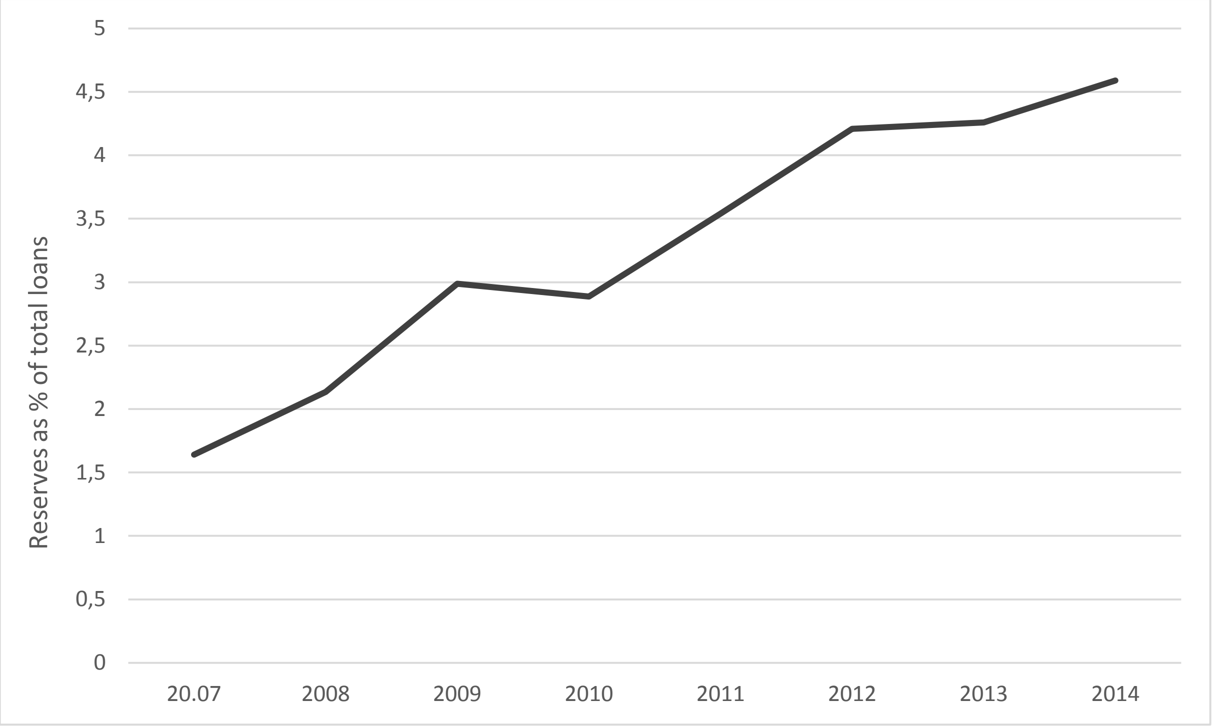
Table 5.4.1 - Regression CRILog, *CDSspread, NonPERF and NetLOAN as dependents*

VARIABLES	(1) CRILog	(2) CRILog	(3) CRILog
CDSspread	-0.000686***	-0.000282***	-0.000266***
	(8.00e-05)	(6.34e-05)	(6.09e-05)
NonPERF		-0.0371***	-0.0375***
		(0.00259)	(0.00364)
NetLOAN			-0.0363
			(0.0351)
Observations	243	164	136
R-squared	0.374	0.793	0.777
Number of CompanyID	42	30	26
Firm FE	YES	YES	YES
YEAR FE	YES	YES	YES

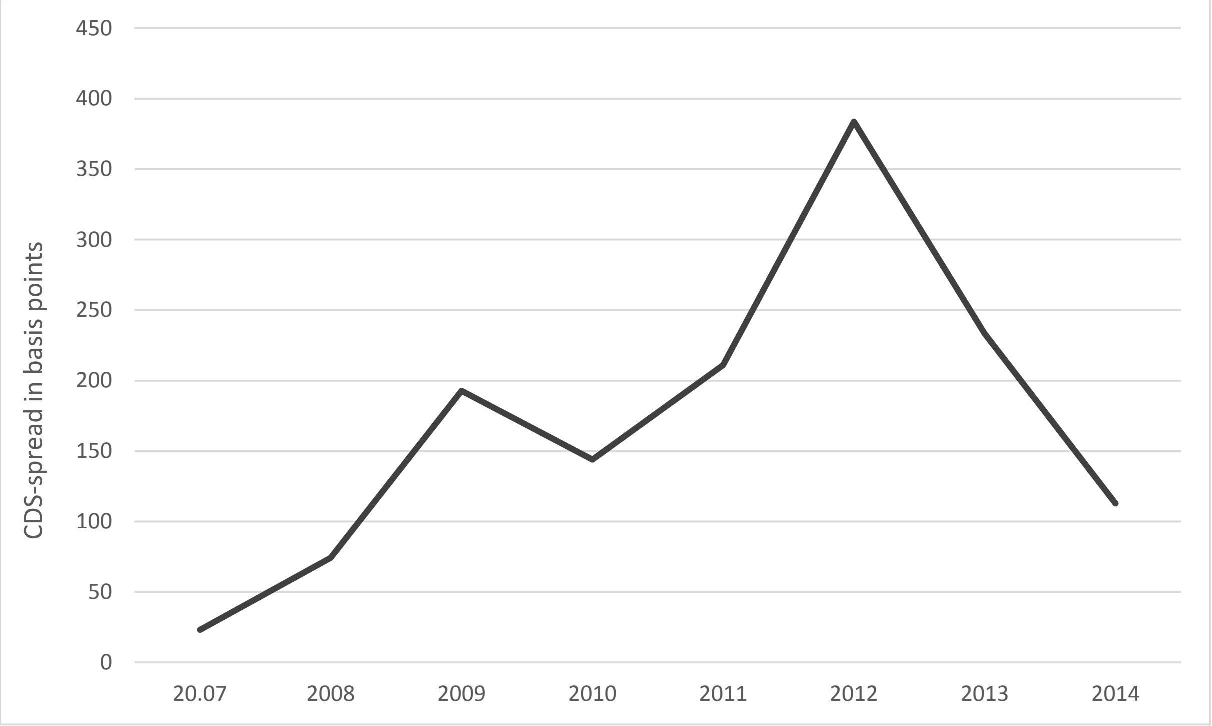
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Graphs

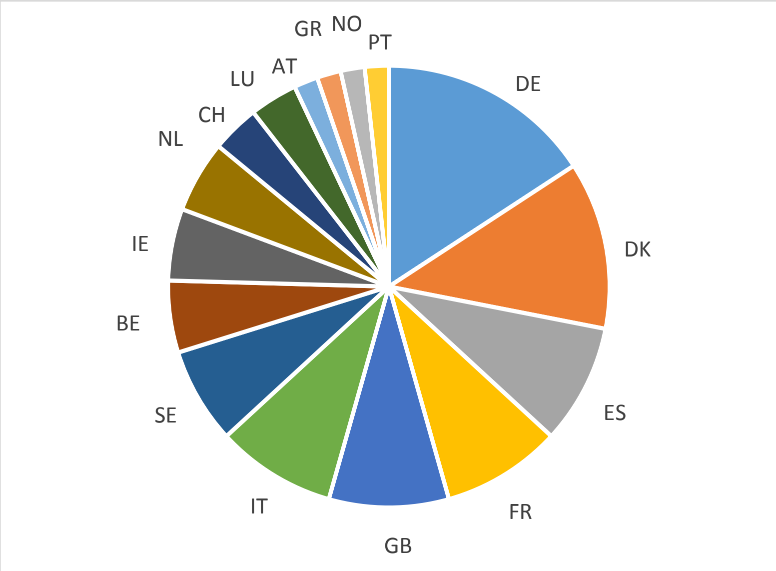
Graph 5.1.5 – Reserves for loan losses as a percentage of total loans, *this graph displays the average Reserves for Loan Losses of the sample over time*



Graph 5.1.6 – CDS-spread in basis points, *this graph displays the development of the average CDS-spreads of the sample over time*



Graph 5.1.7 – Distribution of banks between countries



Country	Nr of banks
DE	9
DK	7
ES	5
FR	5
GB	5
IT	5
SE	4
BE	3
IE	3
NL	3
CH	2
LU	2
AT	1
GR	1
NO	1
PT	1

Figures

Figure 2.5.1 – Risk-weight and PD-relationship, *LGD=45%, FIRB-approach, source Behn et al. (2014)*