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THE CAPITAL REGULATION OF FINANCIAL INSTITUTIONS, THE ROLE OF RATINGS AND THE TENSION FIELD BETWEEN REGULATION AND ECONOMIC REALITY

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Daar de proefschriften in de reeks van de Faculteit Economische en Toegepaste Economische Wetenschappen het persoonlijk werk zijn van hun auteurs, zijn alleen deze laatsten daarvoor verantwoordelijk.

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Publications

Part of this dissertation has led to a publication in an international peer-reviewed academic journal:

Van Laere E.   Baesens B. 2010. The development of a simple and intuitive rating system under Solvency II. Insurance: mathematics and economics. 46(3), pp 500-510. (SSCI: 1.268)

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"The super-boom got out of hand when the new products became so complicated that the authorities could no longer calculate the risk and started relying on the risk management methods of the banks themselves". George Soros, financier, businessman and notable philanthropist - The Financial Times - December 15, 2008

General Introduction

Over the past decade, the economic environment has been characterised by high-profile business scandals and failures, in which different company stakeholders were involved. In July 2007, the world entered the most profound and disruptive crisis since 1929. Initially originating in the US, it has evolved into a deep and complex crisis at global level, resulting in significant economic damage. Lack of market transparency, the abrupt downgrading of credit ratings and the failure of Lehman Brothers have initiated a global breakdown of trust. In autumn 2008 interbank markets shot down, creating a liquidity crisis that is still having a profound impact on the cost and availability of credit, financial markets and the macro-economy as a whole. Both government and Central Banks have taken numerous measures to address the systemic risk and to refuel the economy. However, it has become clear that the regulatory framework and measures in place were insufficient to tackle the crisis. As such, regulatory and supervisory financial authorities are currently confronted with major challenges. In order to understand the current market environment and the challenges these authorities are confronted with, it is crucial to develop a basic understanding of the complex and often intertwined causes of the crisis.

In 2007, the macro-economic environment was characterized by an unusual mix of conditions: low volatility in debt and equity markets, low interest rates, high house prices, rapid innovation in financial instruments, mispricing of risk etc, which eventually resulted in a deterioration of lending standards and increased leverage (e.g. Zingales (2008)). There is little evidence on how lending standards are related to the macro-economic environment; however, Jimenez et al. (2006), Dell'Ariccia et al. (2008) etc. find that during economic booms riskier borrowers obtain credit. In addition to considering higher-risk borrowers, mortgage underwriting standards declined, more risky loan options were offered and borrowing was further incentivized. Moreover, big US investment banks and government-sponsored enterprises were engaging in high-risk lending. So besides low interest-rates, government and competition also contributed to a further increase in high-risk/subprime lending. When these risky mortgages eventually broke down, global markets entered into a credit crisis which soon evolved into an equity crisis, as worried investors liquidated their stocks.

Furthermore, there were huge global imbalances as the credit expansion in the US, where personal savings were negative in 2005 and 2006, was funded by massive capital inflows from emerging countries such as China. In an environment of ample liquidity and low returns, strong global growth and growing capital flows, investors started looking for alternatives with higher yields, resulting in more innovative and complex securitisation practices. However risk was not adequately appreciated and due diligence was not properly observed. The historically low spreads confirm that risks were being mispriced, which was possible due to the opaque securitisation practices. Financial assets were resold and repackaged so frequently that it became impossible to link the product being traded with the underlying value. Even though ample liquidity and low interest rates have been the driving force behind the crisis, it is clear that financial innovation accelerated things.

Another important trigger of the current crisis was the misjudgement of the risk measure- and management practices and quality by financial institutions, regulators and supervisors. The ability of financial institutions to manage their risk was clearly being overestimated with a subsequent underestimation of the level of capital as a consequence. For instance quite a number of financial institutions ignored or misunderstood the interaction between credit and liquidity risk. The inter-bank maturity transformation process which resulted from borrowing in the short term and lending in the long term was not managed with sufficient care. Moreover, the lack of transparency and the complexity of financial innovations made things even more challenging. The nature of transactions often made it impossible to see whether risk had really been spread or whether it had been re-concentrated in less visible areas. This was stimulated by the Basel I framework that encouraged banks to engage in regulatory capital arbitrage practices, taking risk off-balance. Additionally, the originate-to-distribute model[1] created perverse incentives, by blurring the relationship between borrower and lender and by taking attention away from the credit quality of the borrower. On top of this, many board members and senior managers did not understand the products they were exposed to.

Furthermore, Credit Rating Agencies (CRAs), another key suspect of the current crisis, relied on information provided by the originators of structured products when they converted securities from F-rated to A-rated instruments. They regularly gave triple-A ratings to senior tranches of structured products,[2] signalling that these instruments had the same risk levels as standard government and corporate bonds. It is argued that the underestimation of credit default risk largely stems from flaws in their rating methodologies. This was further aggravated by the conflict of interests credit rating agencies were confronted with. The issuer pays model had especially perverse effects in the area of structured finance, where issuers shopped around to get the highest ratings for their products. Earnings for rating these instruments exceeded the rating fee for ordinary corporations by about three times, making the rating of securities a very lucrative and competitive business[3]. This incentive was further stimulated by the fact that certain regulators required investors to limit investments to triple-A-rated investments. In this field, Stiglitz (2009) stresses that banks could not have done what they did without the complicity of the CRAs. However, if CRAs perform at an adequate level of competence and integrity,[4] their services are very valuable in financial markets. At the same time, the use of ratings

[1] Default or credit risk was passed from mortgage originators to investors using various types of financial innovation.
[2] Examples of these instruments are Mortgage Backed Securities based on risky subprime mortgages.
[3] Approx $1.6 trillion in CDO originated between 2003 and 2007.
[4] In December 2008, as a response to recent criticism of their performance, the Security and Exchange Commission approved measures to strengthen supervision of the CRAs.

should never eliminate one's own judgement. A particular failing has been the acceptance by investors of the ratings of structured products without understanding the fundamentals.

On top of this, procyclicality in both accounting and capital requirements aggravated matters. The mark-to-market principle forced financial institutions that had overstretched their leverage to get rid of assets, resulting in fire sales. As ratings of structured products started to decline, risk-weighted capital requirements were adjusted upwards, again forcing banks to sell off assets and further reducing asset prices. Looking for fresh equity in weakened equity markets, banks were obliged to look for government funding and eventually for heavy state intervention. The liquidity problem banks were initially confronted with became a solvency problem.

It is clear that financial institutions play a crucial role in today's globalized economy and that their risk profile has evolved dramatically over the past years, making the financial system much more vulnerable to macro-economical shocks. In light of the recent developments, this research contributes to the fundamentals of capital regulation of financial instructions and the use of internal and external ratings in that respect.

Overview of dissertation papers

Chapter 1: On the road to a safer banking system? Theory and evidence on capital regulation in Europe

Traditionally capital requirements have been the foundation of regulation for banks. To protect banks against failure and to prevent an economic crisis due to contagion and systemic risk, different stakeholders want banks to maintain a certain level of capital. Rating agencies, supervisors and debt holders want higher capital to support solvency, shareholders want lower capital to boost profitability and even the behaviour of other banks might impact the target capital ratio. As a result of these conflicting interests, bank capital needs to be optimized with as a key purpose to internalise the social costs of potential bank failures. Given the continuous evolution in the risk profile of banks, the presumed importance of capital adequacy for financial stability and the agency costs that high capital levels might entail, regulatory authorities are in an ongoing search for optimal capital regulation. In the past, these capital requirements were based on the idea that maintaining a capital buffer allows a bank to remain solvent by absorbing losses. Furthermore these rules were built on the intuition that the solvency of individual banks ensures the soundness of the financial system as a whole. However, the capital adequacy requirements in place have been found inadequate, and as a reaction major steps to move the banking system are currently being taken. Different authorities have started reflecting on these issues and it became clear that we should restate the basic objectives of capital regulation and that we should assess whether the regulatory framework in place is well suited to attain the listed objectives and if not, to make sure it does.

Taking into account these evolutions, it is interesting to know the extent to which recommendations have been adopted and whether the reforms have been and are perceived to be beneficial to the European banking sector. Based on guidance from academics, supervisors and policy makers, we have put together an extensive survey that is used for interviews with various bank managers and chief risk officers from European banks. The first chapter of this PhD presents new evidence on where European banks are with respect to capital regulation and on how the future road to a safer banking system should look like. By commenting on differences and similarities between the financial institutions we have questioned, we will describe the present state of affairs with respect to Basel II implementation, regulatory and economic capital calculations and Basel III expectations. In doing so, we will also address another objective of the Basel Committee, the creation of a level playing field, albeit in an indirect way.

Our results reveal that there is broad agreement on the weaknesses of the current regulation, but that opinions tend to differ quite a lot when it comes to solutions. We believe that banks will benefit from regulatory changes that are grounded in and supported by practice. Consequently, the qualitative insights gained in this paper are key inputs for further optimisation of bank regulation.

Chapter 2: The development of a simple and intuitive rating system under Solvency II

Another type of financial institution that has been both victim and cause in the financial crisis are the insurance companies. Both practitioners and academics have undertaken a substantial body of research on Basel II and more in general on risk management within financial institutions (e.g. Van Gestel et al., 2009). Notwithstanding the fact that insurance companies are very important players in financial markets who are involved in many credit risk exposures and as a consequence are also prone to high levels of uncertainty and solvency issues, literature on the topic is scarce (Florez-Lopez, 2007).

Due to the Solvency II Directive, insurers are currently being confronted with new regulatory requirements that promote internally developed risk models. This evolution emphasises the importance of credit risk assessment through internal ratings. In order to be Solvency II compliant, the internally developed models should be transparent, robust and efficient, creating one of the biggest challenges insurance companies are currently faced with (Carey and Hrycay, 2001; Chorafas, 2004; Grunert et al., 2005), especially because these companies often lack sufficient internal data and modelling experience.

A big challenge in setting up an internal model is the inference of the probability of default (PD). In order to estimate the PD that is linked to an internal rating grade, appropriate techniques must be used. One method of arriving at a transparent result is to associate an internal rating with an external rating and then attribute the external default rate to that internal grade. This mapping must be based on an extensive comparison between internal and external rating criteria. When doing so, it is crucial for financial institutions to understand the external rating process (Brunner et al., 2000; Grunnert et al., 2005) and when possible to align the internal and external rating process and architecture (Carey and Hrycay, 2001).

In light of this new prudential regulation, and taking into account the limited data and modelling experience of insurance companies and the scarcity of academic research on insurance companies, the second chapter of this dissertation suggests a Basel II compliant approach to predicting credit ratings for non-rated corporations and evaluates its performance compared to external ratings. The paper provides an interesting modelling of non-financial European companies rated by S&P. In developing the model, broad applicability is set as an important boundary condition. Even though the model developed is fairly simple and maintains a high level of granularity, it gives high rates of accuracy and is very interpretable.

Chapter 3: Analyzing bank ratings: key determinants and procyclicality

While upgrading financial regulations and supervision in order to prevent future crises, many authorities are being confronted with the fact that risks taken in the process of financial intermediation are difficult to observe and assess from outside the bank. In the absence of tight regulations, this opaqueness exposes banks to runs and systemic risk. In order to reduce this lack of transparency, credit rating agencies (CRAs) provide information that can help various stakeholders to evaluate the credit risk of issues and issuers. Even though CRAs have been criticized a lot in the latest crisis, for many observers of financial markets, credit ratings continue to play an essential role.

Morgan (2002) shows that Moody’s and S&P have more split ratings over financial intermediaries, suggesting that banks are more difficult to rate because of their opaqueness. This additional lack of transparency is linked to the banks’ asset base and their high leverage, which create agency problems and further increase uncertainty over their assets. So far the research linked to ratings of financial institutions is rather limited.

The third chapter of this dissertation presents a joint examination of how different factors influence the assignment of S&P and Moody’s long term bank ratings using a unique data set covering different regions, bank sizes, and bank types. In doing so, we include new bank and country specific variables. Furthermore, we include measures of the business cycle in our analysis to determine whether long term bank ratings tend to be related to the cycle after conditioning on a set of variables. Using annual data on US and European banks rated by S&P and/or Moody's, we find that the bank ratings of both agencies exhibit a different sensitivity to the business cycle. Finally, we check our findings on a sample of banks that are rated by both rating agencies while controlling for potential sample selection bias.

Our findings are highly relevant for various bank stakeholders, who often tend to assume that Moody's and S&P have equivalent rating scales and rating processes. This paper shows clear evidence that this is not the case. Moody's and S&P have different rating determinants, different sensitivity towards the business cycle and behave differently when rating banks that are rated by both of them.

References

Brunner, A., Krahnen, J. P., Weber, M. 2000. Information production in credit relationships: On the role of internal ratings in commercial banking. Center for Financial Studies Working Paper No. 2000/10.

Carey M., Hrycay M. 2001. Parameterizing credit risk models with rating data. Journal of Banking and Finance 25, 195–270.

Chorafas D.N., 2004. Operational Risk Control with Basel II. Basic Principles and Capital Requirements. Elsevier, Amsterdam.

Dell'Ariccia, Giovanni & Igan, Deniz & Laeven, Luc, 2008. "Credit Booms and Lending Standards: Evidence From The Subprime Mortgage Market," CEPR Discussion Papers 6683, C.E.P.R. Discussion Papers.

Florez-Lopez R., 2007. Modelling of insurers' rating determinants. An application of machine learning techniques and statistical models. European Journal of Operational Research 183, 1488-1512.

Grunert, J., Norden L., Weber M, 2005. The Role of Non-Financial Factors in Internal Credit Ratings. Journal of Banking and Finance 29, 509-53.

Jimenez G., Vicente S. Saurina J., 2006. Determinants of Collateral. Journal of Financial Economics 81, 255-281.

Morgan D.P, 2002. Rating banks: risk and uncertainty in an opaque industry. The American Economic Review 92, 874-888.

Stiglitz J.E., 2009. The economic crisis. Capitalist fools.

Van Gestel T., Baesens B., 2009. Credit Risk Management: Basic concepts: financial risk components, rating analysis, models, economic and regulatory capital. Oxford University Press.

Zingales L., 2008. Causes and Effects of the Lehman Brothers Bankruptcy. Testimony before the committee on oversight and government reform.

“The Basel III Framework is a landmark achievement that will help protect financial stability and promote sustainable economic growth. The higher levels of capital, combined with a global liquidity framework, will significantly reduce the probability and severity of banking crises in the future"

Mr Nout Wellink, Chairman of the Basel Committee on Banking Supervision and President of the Netherlands Bank - Bank for International Settlement - December 16, 2010.

Chapter 1: On the road to a safer banking system? Theory and evidence on capital regulation in Europe*

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Abstract

In order to promote financial stability, regulatory authorities pay considerable attention to capital regulation. The current crisis has revealed that we should restate the basic objectives of financial regulation and that we should assess whether the regulatory framework in place is well suited to attain these objectives and if not, to make sure it does. This paper presents new evidence on where European banks are with respect to capital regulation and on how the future road to a safer banking system should look like.

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1.1 Introduction

Financial institutions play a crucial role in today's globalized economy. Because of their expertise and by monitoring and screening potential borrowers, these financial intermediaries have a comparative advantage in overcoming asymmetric information (Diamond, 1984). As such, one of the fundamental roles of these financial intermediaries is capital allocation by lending funds that have been deposited in their accounts. These deposits are subject to a "first-come-first-serve" rule. In a negative environment with rumours about the bank holding low quality assets, this could eventually lead to bank customers withdrawing their deposits because they fear bank insolvency (Diamond and Dybvig, 1983). Much of the Great Depression's economic damage was caused by bank runs and the current financial crisis also shows the negative impact on financial stability of these events (e.g. Northern Rock UK, Sept 2007; Washington Mutual US, Sept 2008; Landsbanki Iceland, Oct 2008).

To a great extent financial institutions are typically confronted with credit, market and operational risk. The default history of financial institutions shows that credit risk is the most important threat to bank solvency. Recent evolutions, such as disintermediation by highest quality and largest borrowers**,** a declining value of real assets (and thus collateral) in many markets (e.g. Altman and Suggitt, 2000)**,** dramatic growth of off-balance sheet instruments with inherent default risk and a structural increase in the number of bankruptcies (e.g. Wheelock and Wilson, 2000), make these risk factors more complex than ever before (see Carey and Stulz, 2005). This is reinforced by the fact that in recent years we have experienced an unusual mix of conditions[5] resulting in a deterioration of lending standards and increased leverage (e.g. Zingales, 2008). As a result of these developments, the risk profile of financial institutions has evolved dramatically over recent years and the financial system has become much more vulnerable to macro-economic shocks (e.g. Schuermann and Stiroh, 2006).

In autumn 2008 the interbank markets shut down, creating a liquidity crisis that is still having a profound impact on the cost and availability of credit and is impacting the financial markets and the economy as a whole. It became clear that the boards and senior management of banks had difficulties in appreciating the magnitude of the risks taken by their institution, and that they understood the implications of these risks even less. Furthermore, it quickly showed that to effectively manage or avoid another systemic crisis, many measures would be necessary and a thorough review of the regulation in place was necessary. Because of the complexity and the scope of the problem, there is a tendency to further complicate already sophisticated market rules. In a reaction, there is a trend from other regulators to introduce revolutionary proposals as an attempt to simplify the regulations. The re-

[5]Some examples of these conditions are low volatility in debt and equity markets, low interest rates, high house prices, rapid innovation in financial instruments such as innovative mortgage options etc.

actualisation of the Glass-Steagall Act[6] and the effort of the American government to address the too big to fail paradigm are two examples of these attempts.

Traditionally capital requirements have been the foundation of regulation for banks. To protect banks against failure and to prevent an economic crisis due to contagion and systemic risk, different stakeholders want banks to maintain a certain level of capital. Rating agencies, supervisors and debt holders want higher capital to support solvency, shareholders want lower capital to boost profitability and even the behaviour of other banks might impact the target capital ratio. As a result of these conflicting interests, bank capital needs to be optimized with as a key purpose to internalise the social costs of potential bank failures. Given the continuous evolution in the risk profile of banks, the presumed importance of capital adequacy for financial stability and the agency costs that high capital levels might entail, regulatory authorities are in an ongoing search for optimal capital regulation. In the past, these capital requirements were based on the idea that maintaining a capital buffer allows a bank to remain solvent by absorbing losses. Furthermore these rules were built on the intuition that the solvency of individual banks ensures the soundness of the financial system as a whole. However, the capital adequacy requirements in place have been found inadequate, and as a reaction major steps to move the banking system are currently being taken.

Taking into account these evolutions, it is interesting to know the extent to which recommendations have been adopted and whether the reforms have been and are perceived to be beneficial to the European banking sector. Various parties seem to know how bank regulatory reforms have been implemented and, at least before the summer of 2007, often draw optimistic conclusions about the changes. However, do we really know how banking policies have changed in the recent years and is there any clear evidence on the impact of the reforms? Did the changes of Basel II and will the changes of Basel III really contribute to the creditworthiness of banks and financial stability? These questions represent an important area of investigation. Based on guidance from academics, supervisors and policy makers, we have put together an extensive survey that is used for interviews with various bank managers and chief risk officers from European banks. Our survey has 45 different respondents covering 15 countries between January 2008 and July 2010[7]. The opinions of the 45 banks will be compared to different viewpoints from academics and opinion leaders on the one hand and the regulators and supervisors on the other hand.

[6] The Glass-Steagall Act, also known as the Banking Act of 1933, is based on the idea of an incompatibility between investment banks and commercial banks and basically prohibits commercial banks from engaging in the investment business (See Barth et al., 2000).

[7] As rumours of a Basel III only emerged during the second half of 2009, the interviews that took place before mid-2009 did not address the Basel III issues.

Before setting the scene, we will elaborate on two key inputs for bank regulation, regulatory and economic capital. Experience has shown that one of the most important failures in bank regulation is the fact that regulations lag behind and diverge from economic reality. As a result the key objective of Basel II has been to further align regulatory capital - the minimum capital level enforced by regulation - and economic capital - the amount of capital necessary to support the real economic risk a financial institution faces -. In order to really understand what went wrong it is important to develop a thorough understanding of both capital numbers. In a subsequent section we will set the scene in Europe. By commenting on differences and similarities between the financial institutions we have questioned, we will describe the present state of affairs with respect to Basel II implementation, regulatory and economic capital calculations and Basel III expectations. In doing so, we will also address another objective of the Basel Committee, the creation of a level playing field, albeit in an indirect way.

This paper addresses a number of important gaps in academic literature. Even though there is an extended literature about capital regulation, there is no paper that gives an overall picture of the determinants and challenges of both economic and regulatory capital under Basel II. Furthermore, the existing literature on economic capital is limited and the comparison to regulatory capital is practically unexplored[8]. By filling this void we hope to offer new insights in the room for regulatory capital arbitrage that currently exists. So far, the impact of Basel II on financial stability has been estimated by different techniques, but the true impact of Basel II has not yet been investigated. In addition, at this point no clear picture of Basel III expectations has been set. Furthermore, there is no paper that has combined the different viewpoints of the different actors in the banking sector. However, doing so provides unique insights into where Europe stands in terms of capital regulation and how it should proceed on the road to a more stable financial system. Our results reveal that there is broad agreement on the weaknesses of the current regulation, but that opinions tend to differ quite a lot when it comes to solutions. We believe that banks will benefit from regulatory changes that are grounded in and supported by practice. Consequently, the qualitative insights gained in this paper are key inputs for further optimisation of bank regulation.

This paper is structured as follows. Section II gives a comprehensive literature review discussing the role of capital adequacy and the differences and similarities between economic and regulatory capital. We will look at the current state of bank capital regulation and its evolutions here. In Section III, we will discuss the current European banking landscape and the data. In section IV theoretical expectations are contested with empirical findings. For every topic, we try to address the bankers' view, regulator's opinions or academics' and opinion leaders' perceptions. This unique confrontation

[8] To the best of our knowledge, only Elizalde et al. (2006) theoretically compare economic to regulatory capital and Liebig et al. (2007) empirically compare economic and regulatory capital, however they use estimations rather than real capital numbers in their analysis.

allows us to identify future points of friction and areas of agreement. The last part of this paper draws the conclusions that should be taken as key take-away points for further development of the banking sector regulation.

1.2 Bank Capital: usefulness and regulation – theoretical framework

1.2.1 Bank capital and capital regulation – usefulness

Before moving to the underpinnings of regulatory and economic capital calculations, it is important to develop an understanding about the usefulness of capital regulation and bank capital. These insights underscore the relevance of investigating the impact of the Basel accords on financial stability.

The ultimate goal of financial institutions is to maximize shareholder value taking into account the different restrictions and obligations they are confronted with, and thus not blind compliance with regulatory measures. As such it is highly debatable whether a risk based capital ratio is the ideal tool to mitigate bank risk (e.g. Berger et al., 1995). The capital in the numerator is difficult to measure and may not always control moral hazard incentives, and the denominator also appears difficult to measure and even under Basel II can be considered to be only a weak reflection of risk. The lack of consensus is mainly induced by differences in opinion with respect to the objectives and implications of capital regulation, but also by the unique characteristics of banks. Banks can create liquidity because of the fact that deposits are fragile and prone to runs. This fragility increases with uncertainty, creating a role for bank capital. So, more bank capital reduces the probability of bank default, but at the same time it dampens liquidity creation (Diamond and Rajan, 2000).

There is an extensive literature on the role of capital regulation as a determinant of bank capital structure. The results in empirical banking literature are rather mixed. Benston and Kaufman (1996) and Dowd (1999, 2000) argue that capital regulation is both unnecessary and incapable of improving banks' capital position more than banks could do on their own. In Dowd's view, shareholders can enforce proper risk behaviour. Flannery and Ranjan (2002) show that the observed increase in capital in US banks, especially in the second half of 1990s, can be explained to a large extent by market discipline. Over the past decades, banks' counterparties have become more aware of their exposure to a bank's default risk. Also Marini (2003) argues that market-determined levels of bank capital can substitute for regulatory oversight. Previous empirical studies investigating the impact of regulations on equity in the 60s and 70s (Dietrich and James, 1983; Mingo, 1975; Peltzman, 1970), also found that regulations did not have an impact on capital levels. Mingo (1975) is an exception. Yet, Dietrich et al. (1983) show that Mingo's findings of significant regulatory influence is a proxy for binding deposit rate ceilings, which led banks to increase capital to lure depositors. In more recent work, the level of capital a bank maintains is found to be a function of public policy, bank regulatory characteristics, bank specific variables and/or macro-economic conditions. Brewer et al. (2008) find that several country and policy variables are highly significant for the level of capital a bank maintains. However, a recent paper by Gropp and Heider (2010) suggests that capital requirements may only be of secondary order for bank's capital level and show that a bank's capital structure is stable and specific to each bank.

But even when regulations have an impact on the capital levels banks maintain, it is unclear whether increased ex-ante capital requirements do indeed reduce systemic risk. This is especially relevant taking into account that regulations tend to pay a lot of attention to the narrow objective of reducing individual bank failure rather than to credit crunch externalities (Kashyap and Stein, 2004). Blum (1999) argues that capital adequacy requirements might not reduce risk. Kahane (1977), Koehn and Santomero (1980) and Kim and Santomero (1988) show that the effect of bank capital on overall safety depends on risk aversion across banks. More stringent capital requirements could make the banking system as a whole more or less risky.

It is generally accepted that tighter capital regulation will result in credit rationing in the short run, whereas in the long term it might increase total lending due to the increased capital cushion. However, there is a clear lack of consensus in literature about the effects of capital requirements on bank behaviour. The basic idea is that tighter capital requirements imply higher losses for the banks' shareholders in case of default, and hence lower incentives for risk-taking. Van Hoose (2007) gives an overview of theoretical models predicting the effect of capital regulations and shows that the overall effect on bank safety and soundness stays ambiguous.

Koehn and Santomero (1980), Keeton (1988) and Kim and Santomero (1988) show that a relative increase in equity can have both a positive (increase) and negative (decrease) effect on the bank portfolio risk. However Furlong and Keeley (1989) only found a negative effect on portfolio risk for value maximizing banks with publicly traded stocks. This was again contested by Gennotte and Pyle (1991) under the assumption of decreased return on investment. Lane et al (1986), Avery and Berger (1991), Cole and Gunther (1995) empirically show a negative relation between the level of equity and the risk profile of a bank. However Thomson (1991) argues that the level of equity has no direct effect on bank performance. Hellmann et al. (2000) claim that in addition to the "capital at risk" effect, there is a franchise value effect, that goes in the opposite direction. More specifically they show that higher capital requirements reduce the banks' franchise values, and hence the payoffs associated with prudent investment, so that their overall effect is ambiguous. In a later paper, Repullo (2004) shows that for a particular model of imperfect competition in the deposit market, bank capital requirements are in general effective in preventing banks from taking excessive risks.

John et al. (2000) argue that capital regulation might not be the ideal tool to control risk. They show that the effectiveness of capital regulation depends on the available investment opportunities. More recently, Jeitschko and Jeung (2005) have investigated the link between agency theory and the risk-bank capital relationship. As can be expected they find that the incentive effects of bank capital depend on the agent that dominates portfolio decision making. This is in line with some previous work of Rochet (1992) who shows that the effect of capital requirements on risk-taking is ambiguous when the bank's investment decision is taken by a risk averse owner-manager and concludes that capital requirements are insufficient to control for moral hazard. Looking at the impact of the adverse selection problem on the importance of bank capital, Morrison and White (2005) find that an unregulated banking system can only be efficient when the monitoring cost is small. However, it is clear that if banks respond to capital regulation by making riskier asset choices, the capital cushion will disappear. Barth et al. (2010) find that greater capital regulation stringency is marginally and positively associated with bank efficiency.

More recently, the combined effects of capital regulation and the two additional pillars of Basel II have been investigated (infra). Rochet (2004) argues that rather than implementing an extremely complex regulation that will ultimately be bypassed by the largest or most sophisticated banks, banking authorities should keep close relationships with bankers and that supervisors should control the behavior of banks in distress. More specifically he openly questions the emphasis that is currently put on risk-based capital as the ultimate tool to obtain financial stability.

It is clear that the institutional and/or economic environment in which a bank operates has an impact, either to a big or lesser extent, on bank behaviour and the capital levels they maintain. Even though a lot of ambiguity on the role of capital continues to exist, regulatory capital stays a key input in bank regulation. Furthermore, the role of capital requirements under Basel II and Basel III cannot be restricted to a safety buffer against unexpected shocks. It is expected that it will create a change in risk culture in financial institutions all around the world by encouraging improvements in the quality of risk management practices and because of this fact capital reserves are expected to better reflect potential deterioration in expected losses. In the next paragraphs we will elaborate on the regulatory capital and its current form.

1.2.2 Regulatory capital and its evolution over the past decade

Financial institutions are able to forecast the average risk and associated credit loss of their assets; these expected losses (EL) are part of doing business and should be covered by the pricing of assets. The unexpected losses (UL), losses that exceed expectations, should to a certain extent be covered by bank capital. An important concern of the authorities who set capital requirements is safe deposits and the protection of the economy against systemic risk (Sharpe, 1978). By imposing high capital levels, small investors are protected and potential systemic effects of bank failure are countered. However, extremely high capital requirements might create efficiency costs (Jackson et al. 2002) such as the diversion of financial resources from their most productive use, artificial incentives to take off-balance sheet risks etc. To prevent negative consequences of setting inaccurate capital requirements, regulatory authorities should take into account this trade-off.

New financial regulations tend to arise to address a void that some previous crisis has exposed. The Bank for International Settlements plays a central role when it comes to this new banking capital regulation. The Basel Accords are issued by the Basel Committee on Banking Supervision which is composed of representatives from central banks and regulatory authorities of the Group of Ten countries plus others. Even if this committee does not have the power to enforce its recommendations, most member countries tend to implement the committee's policies, by transposing them into national (or union-wide) laws and regulations. This is the reason why the implementation might vary in essence and in timing from one country to another.

1.2.2.1 Basel I

The first Basel Accord (Basel I) was a response to the crisis of 1974. It was issued in 1988 and capital regulations came into force in December 1992, with two main objectives, namely requiring banks to maintain enough capital to absorb losses without causing systemic problems and levelling the playing field internationally in order to avoid competitiveness conflicts. The minimum ratio was set at 4% for Tier 1 capital to risk-weighted assets and 8% for Tier 1 and Tier 2 capital. Under Basel I, there was a big gap between economic risk of an exposure and the risk measure incorporated in regulatory capital. As such, a lot of banks removed low-risk assets from their balance sheets and only retained relatively high risk assets on balance, with a negative impact on financial stability (Avery and Berger, 1991; Jones 2000). Most of the off-balance sheet vehicles were motivated primarily by regulatory arbitrage, that is, by the desire to avoid the regulatory requirements imposed on banks. The off-balance sheet vehicles had little or no capital and little or no transparency. When an opaque bank invests in opaque financial instruments, systemic risk is increased. The major downside of this so-called regulatory capital arbitrage (RCA)[9] is that reported ratios could mask deterioration in the true financial conditions of a bank (e.g. Keys et al. 2008). Furthermore as accessibility to RCA depends on economies of scale and scope and on international differences with respect to legislation, supervision etc. it might increase competitive inequalities and as such reduce the level playing field (Jones, 2000).

[9] Regulatory arbitrage refers to the fact that a bank takes advantage of the difference between regulatory and economic capital. If the true risk of a bank asset is higher than the regulatory weight, the bank will have an incentive to keep these assets on balance. However if the true risk is lower, the bank will remove the asset by means of securitisation. As such, the presence of regulatory arbitrage will increase the overall risk of financial institutions.

Concerns about the possible extent of arbitrage actions under Basel I encouraged the Committee on Banking Supervision to revise the existing framework and in 1999 the first consultative paper on Basel II was published.

1.2.2.2 Basel II

The second Basel Accord was further fine-tuned as a solution to the crisis of 2000. Compared to Basel I, Basel II presents more comprehensive guidelines which aim to make capital allocation more risk sensitive, adding operational risk in credit risk management and introducing internal models. The major objective of Basel II is to further align regulatory capital with the economic capital demanded by its different counterparties in a way that does not harm the level playing field (BCBS, June 2006; Gordy and Howells, 2004). Under Basel II the numerator remains unchanged at 8% of RWA, consisting of at least 50% of common stocks and retained earnings (Tier 1 capital). These funding sources are available to absorb potential losses and are considered the most reliable and liquid. Tier 2 capital, which mainly consists of subordinated debt and general provisions, but also includes undisclosed reserves, revaluation reserves and hybrid instruments, is far less reliable (see Berger et al. 1995).

The Basel II framework is based on three reinforcing pillars. Pillar 1 defines new risk-based requirements for credit risk and a new charge for operational risk, Pillar 2 sets requirements for supervisory review and introduces the concept of economic capital into the regulation, and Pillar 3 is related to market discipline and the associated disclosure standards. In this article the focus is on pillar 1 and pillar 2 and more specifically on the regulatory and economic capital requirements for credit risk. Within this framework, there are two approaches to calculating the regulatory capital requirements. Under the standardised approach, the risk weights depend on an external rating provided by an external credit rating agency. The standardised approach is conceptually quite similar to Basel I; it is more risk-sensitive but there is still insufficient differentiation among creditors. As the capital requirements for the investment grade facilities remain too high and those for the noninvestment grade facilities too low, the incentive for regulatory arbitrage will continue to exist. Under the internal rating based (IRB) approach there is much more differentiation in credit risk and as such it should significantly reduce the incentives to engage in regulatory capital arbitrage. Under this approach banks are allowed to determine the values for certain risk parameters based on internal models. An important issue for the strength of the IRB approach is the reliability of the parameters banks provide. By using the internal risk assessments of banks for setting capital requirements, the IRB approach promotes the adoption of stronger risk management practices by the banking industry. The internal systems used for regulatory capital should meet certain criteria and supervisory approval. In this view, the IRB approach can be regarded as a compromise between a purely regulatory measure of credit risk and a fully internal model based approach[10]. In 2000 already, Carey stressed that the success of Basel II in matching economic and regulatory capital will depend on the degree to which the IRB approaches will take into account portfolio differences related to maturity, granularity and risk characteristics.

The Basel II focus on making prudential capital more closely aligned to the banks' own economic capital has not restrained bank expansion in good times nor could it offset the latest implosion of the financial system as a whole. As such, at the start of the crisis it became clear that Basel II, even when not implemented fully, had shortcomings on many aspects. These shortcomings include no concentration penalty, a single global risk factor, pro-cyclicality, ignorance of counterparty risk and contagion, unclear and inconsistent definitions of capital, the failure to capture on and off balance sheet risks etc. The pre-crisis capital standards were too weak for the types of risk that emerged. In July 2009 the Basel Committee already modified the accord in order to boost the capital held for market risk in the trading book portfolio. Later in December 2009, the committee issued a new document addressing some of the issues noted above.

1.2.2.3 Basel III

The Basel Committee is now working on a new accord, whose ultimate goal is to fundamentally strengthen global capital standards. This newly drafted accord entails some important modifications that can be summarised as follows: a tighter definition of tier one capital, a framework for counter-cyclical capital buffers, measures to limit counterparty credit risk, the introduction of a leverage ratio and short and medium-term quantitative liquidity ratios.

More specifically, Basel III has a strong focus on common equity, which should from 2015 onwards amount to a minimum of 4.5%. Similarly tier 1 minimum capital requirements will be increased to 6%. On top of this, by 2019, banks will be required to hold a capital conservation buffer of 2.5% of common equity to further strengthen their position in times of distress. Besides the level of capital, the denominator of the capital ratio will also further improve. More specifically, as of the end of 2011, higher capital requirements for trading books and complex products will be a fact. To avoid excessive leverage in the system, to back the risk-based capital requirements and to address model risk, the risk based capital measure will be complemented with a leverage ratio, which is now set at a minimum of 3% of tier 1. It is further stressed that depending on their risk profile, economic conditions, business models etc. banks should hold sufficient capital well above that minimum level. As such, supervisory control and intervention under Pillar II will continue to be key inputs in the new rules. More specifically, to address the issues concerning 'proportionality', the Basel Committee and the Financial Safety Board are developing an integrated approach to systemically important (too-big-to-fail)

[10] For an overview of the input parameters of the Basel II IRB capital formula we refer to appendix 1.1.

financial institutions which could include combinations of capital surcharges, contingent capital and bail-in debt.

To tackle system-wide risks, Basel III will promote the build-up of buffers in good times, for example by the countercyclical capital buffer which has been calibrated in a range of 0-2.5%, and falls under the judgment of national authorities. This measure is part of the broader macro-prudential goal of protecting the banking sector from periods of excess credit growth that have often been associated with the build-up of system-wide risk. Furthermore it has been agreed that systemically important financial institutions should have a loss absorbing capacity beyond the common standards. After a smooth transition this should eventually result in a considerable increase in the quality and level of bank capital and in doing so, reduce the systemic risk. Besides the new capital requirements, Basel III is also introducing new global minimum liquidity standards defined as the liquidity coverage ratio and the net stable funding ratio. The liquidity coverage ratio (LCR), which will require a bank to hold enough highly liquid assets to cover 30 days of net cash outflows, will become a minimum global standard in January 2015. The net stable funding ratio (NSFR), which covers a bank's longer-term liquidity and requires a minimum amount of funding that is expected to be stable over a 1 year horizon, will become mandatory in January 2018. The main idea behind the liquidity standards is to ensure that banks have sufficient liquid assets to withstand a shock loss of access to funding markets.

The proposals for capital reform do make improvements with respect to some aspects of the capital management process under the Basel II regime. However, the trade-off between benefits and costs seems difficult to achieve; every party (bankers, regulators and academician/opinion leaders) admit that there is a need for new regulation but at the same time try to defend their individual future interests. Bankers fear that the new regulations will be too strict and will negatively impact the availability of credit and thus global economic growth. The EACB[11] further expresses its concern about the regulations at European level (CRD V). Overregulation at European level would result in a competitive disadvantage for European banks compared with Asia and the US, again increasing room for regulatory arbitrage. Furthermore the EACB warns against the use of the leverage ratio, as it does not estimate risk adequately and in their view even stimulates risky behaviour, because there is no common knowledge on what a healthy ratio would be. Another important deficiency of Basel III is the risk weighting of assets. We entered a financial crisis because assets that were full of worth suddenly became worthless. With this in mind, regulators should reconsider their way of treating assets on a bank's balance sheet in a more detailed way. Few opinion leaders disagree, however, with one of the main points of the Basel Committee and its reason of existence, the idea of globalised regulation. They argue that it reduces banks' diversification and reinforces the excess of financial globalization.

[11] The EACB is the European Association of Co-operative Banks and represents the voice of co-operative banks in Europe.

However at the same time it is clear that the first changes and improvements should take place on a local level.

Now we have developed an understanding of the calculation, objectives and usefulness of regulatory capital, the next paragraphs will go more into detail on economic capital.

1.2.3 Economic capital

1.2.3.1 Economic capital: definition and use

Besides the regulatory requirements, financial institutions calculate their own economic capital reflecting unexpected losses and true risk according to the specific characteristics of their portfolio (Jackson et al., 2002). Economic capital can be defined as the amount of capital necessary to support the real economic risk a financial institution faces at a specified confidence level and over a given time horizon. Different degrees of risk aversion will lead to a different economic capital.

Over the past years, the notion of economic capital has broadened from risk and performance measurement to the determination of bank capital adequacy. This evolution is partly induced by the rapid changes in risk quantification and greater complexity of portfolios. In addition, pillar 2 of the Basel Accord, where supervisors want banks to rely on internal models to assess capital adequacy, has contributed to this. Pillar 2 is directed at regulatory review and internal risk assessment, investigating the extent to which best practices in risk management are an integral part of decision making (Alexander and Sheedy, 2008).

Economic capital coexists with accounting and regulatory capital. It is mainly used for internal risk management purposes, but has different applications. Depending on the objectives of the tool and availability of data, a different methodology is required. The relevance and usefulness of economic capital depends on the extent to which senior management realises the importance of the economic capital measures (BCBS, 2008).

Economic capital typically covers credit risk, market risk (including interest rate risk), operational risk, concentration risk and is sometimes extended to business/strategic risk, counterparty risk, insurance risk, model risk etc. The individual risk components are often estimated while ignoring potential interaction effects between them. Besides the interaction effect, differences in horizons, confidence levels etc. might also bias the calculations (BCBS, 2008). One of the major challenges in economic capital calculation is risk aggregation. This is also a fundamental problem of pillar 2, as from a regulatory point of view there are no clear guidelines to the methodology that should be employed on, for example, how to integrate risk effects. In light of the recent crisis, a crucial question is the nature of the integrated risk methodology that was used by banks for economic capital calculations. Kretzschmar et al. (2010), argue that the introduction of integrated economic-scenario-based models[12] are necessary to further improve capital adequacy, enhance Pillar 2's use and invigorate the importance of the Basel regulatory framework.

1.2.3.2 The difference between economic and regulatory capital

Economic and regulatory capital are both a reflection of the risks embedded in transactions. The prevalent differences between both capital numbers, are partially induced by the different objectives regulatory and economic capital target, i.e. financial soundness and optimization of business strategies respectively. It is important to keep in mind that neither under Basel II nor under Basel III is regulatory capital a substitute for economic capital or vice versa (Araten, 2006, Burns, 2005, Elizalde et al., 2006; Jackson et al., 2002; Jacobson et al. 2006). Regulatory capital is estimated at a transaction level based on risk weighted assets with probability of default (PD), loss given default (LGD), exposure at default (EAD) and remaining maturity as inputs. It is designed to guarantee the stability of the entire system and is thus more conservative in certain aspects. The credit risk economic capital framework can recognise concentration risks and diversification benefits that arise from regional and industrial diversification. Furthermore, the credit risk EC framework can be value-based, where it does not only take into account default, but also up and downgrades. In economic capital the additional risk drivers can be taken into account and for EC calculations no caps and floors are required for risk drivers. As a result EC should be a better reflection of the actual risks embedded in the transaction than regulatory capital. The interviews we have conducted (infra) show that there are big differences in the way banks are addressing economic capital. In some banks it has gained considerable acceptance over recent years, in others it is in its infancy or still not part of their strategy. But those banks that are already more advanced, also use different techniques, include different kinds of risks etc. The final calculation of economic capital within a financial institution and the observed differences with regulatory capital will of course depend on the model that is used and on the parameterization of model inputs. For a detailed comparative analysis of the existing credit risk models we refer to Allen et al. (2004) and Crouhy et al. (2000). Figure 1.1 gives an example of potential differences between both capital numbers.

Insert Figure 1.1 here

[12] In the fully-integrated approach, correlations are due to common dependencies in the driving risk factors in global markets. The modular approach, which is currently also allowed under pillar 2, uses a correlation matrix overlay to account for

The theoretical overview in the previous paragraphs shows that even though the regulatory framework should result in a further convergence between regulatory and economic capital, they continue to have different determinants. Both capital numbers move in the same direction, but not with the same slope and speed. Furthermore the expected impact of capital regulation on financial stability stays ambiguous. However, where Basel I offered a leeway for capital arbitrage by choosing higher-risk assets within each risk category, Basel II and III ought to offer fewer possibilities for regulatory arbitrage and as such should increase financial stability. At the same time it is clear that the room for capital arbitrage will still exist and much will depend on the way the rules are currently interpreted and implemented.

In the next part of this paper we will look at how European banks operate and manage their risk and capital in practice.

1.3 Bank Capital: usefulness and regulation – evidence from Europe

In this paper we will look at whether and how European banks adjust their behaviour in line with the regulatory framework. More specifically, based on several interviews, we will develop an understanding of current practices with respect to risk management, internal rating models and regulatory and economic capital. This will allow us to set the current European scene. As banks have only started implementing Basel II since 2007 and rumours about Basel III only emerged at the end of 2009, real data has only recently become available. All the previous empirical papers that look at the expected effect of Basel II on financial stability (e.g. Griffith-Jones, 2003; Liebig et al. 2007; Reisen, 2001) use approximated capital numbers and not real capital numbers. As Basel III will only be enforced at a later stage and the current framework was only decided upon in the second half of 2010, most of our findings are based on Basel II. However, where appropriate we will make the link to Basel III and we will also report on the expected benefits and drawbacks of the new framework. To the best of our knowledge, this is the first paper to address this issue in a qualitative manner after Basel II implementation and the heart of the crisis.

In order for policymakers, regulators and bankers to draw valid conclusions, it is important to get a clear picture of the banks that collaborated in this survey. As such in the next paragraphs we will elaborate on the European banking structure and the banks that collaborated.

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dependency between different asset class risks. Kretzschmar et al., 2010 show that precisely in periods of stress, capital derived using a correlation matrix diverges from the fully-integrated framework and results in undercapitalized banks.

1.3.1 Data & Methodology

As stated, the goal of the research is to compare the views of the opinion leaders/academics, regulators and bankers. A specific procedure had been used for each of these parties; this is in order to adapt to the specificity of the interlocutors and also to maximize quality of the outcome. In appendix 1.2 you can find an overview of the different parties involved. As European bank managers form the heart of our study, we will further elaborate on them below.

1.3.1.1 European Banking Landscape

In the second half of 2007, the profitability of the European banking sector decreased a lot and the banks' financial health further deteriorated in the course of 2008. The bank's operating income, expressed as a percentage of their total assets, fell significantly (ECB, 2009). Due to the worsening of macroeconomic conditions in the first half of 2009 and taking into account that loan loss provisioning costs tend to rise with some lag it is not surprising that anno 2010 things have not recovered.

However it is important to keep in mind that there are important differences between banks and countries. The European banking landscape is characterised by very diverse banking structures. Domestic banks differ significantly from one country to another, for example in terms of type, activity, size and rating. As a consequence, supervision very often remains at a national level. These different banking formations also induce difficulties in the centralization of a European or global banking regulation (see Barth et al., 2001, 2008). Furthermore, in order to prevent weaker banks from going bankrupt, there has been a wave of mergers and acquisitions that have resulted in most countries having a limited number of small "champions" left. These banks have evolved into institutions that are too big to fail, too big to monitor and in some countries perhaps even too big to save (e.g. Iceland) (Brunnermeier et al., 2009).

The diverse landscape implies that, for instance, the split-up in Germany is different from the one in the U.K. In Germany the landscape for retail banks mainly consists of non-profit savings and cooperative banks (Ayadi et al., 2009) whereas these bank types have typically been replaced by commercial banks in the U.K. Another characteristic of the German banking sector is that the government owns 42% of the banking sector, a relatively high amount in the European banking population. Germany has much more of a bank-based financial system and is quite different from other European banking structures (Ayadi et al., 2009). It is a country that accounts for one third of the total amount of banks in the European Union and is characterised by a massive amount of local savings banks. These are often tied to one specific region or Bundesland and leave few deposits available for the biggest commercial banks (e.g. Deutsche Bank). Only 12% of total deposits are held by these banks, which is quite low compared to the Netherlands where over 80% of all deposits are placed with the five largest banks. The Netherlands is also the only European country that has a bank with an AAA-rating. And then there is Luxembourg, a typical European financial centre with hardly any domestic banks (95% of banks are foreign owned) and a major asset management administration competency. Both characteristics imply that we can hardly use these banks to compare loosely with others. Firstly because the national banking sector will mainly consist of foreign branches, secondly because investment management firms are less subject to Basel requirements. This is the result of their major off-balance sheet activities and because of the fact that no common equity is needed, since the risk is with the client rather than at the financial institution.

To some extent the United Kingdom is also a remarkable country in Europe. The Anglo-Saxon point of view is typically different from the continental European view. The common-law system, the limited government ownership of banks and the capital London as a major worldwide financial centre with a strong concentration of investment bank headquarters have a strong influence on the British banking landscape. Barth et al. (2008) concludes a zero ownership by the government, but after the recent crisis and Lloyds TSB's & RBS's bailout this has changed. In southern Europe, both Greece and Spain are remarkable countries. Greece has the least banking institutions per capita in the E.U. Moreover, the sector has been heavily affected in the last few months by the government's fragile debt position. Spain is to some extent similar to Germany, because of its cajas (saving banks). The country also has a typical example of a big European bank that survived the crisis really well – Santander – and is still one of the top rated (AA) retail banks in Europe. The Spanish government does place restrictions on universal banking, which could lead to other interesting results.

The banking sector in Eastern Europe is quite different from the rest of Europe. Like many former communist countries, Hungary has a relatively young private banking sector (Majnoni et al., 2003). The reforms launched in the 1960s and 1980s and the resulting moves towards a more open economy have shaped the development and the ownership structure of the Hungarian banking system. Hungary has chosen a path that has led to a relatively large degree of foreign ownership in the banking sector. According to the Bank of Slovenia (2008), the commercial banks in Slovenia account for a prevailing proportion of about 70% of the Slovenian financial system's assets. This is significantly more than in other countries (57% on average), where insurance plays a bigger role. Also Scandinavian countries have their specificities and historical background. It could be that banks located in Scandinavian countries, are more prudent or have a different view on how the new regulation should be as a consequence of their different geographical location and culture.

As we pursue the survey in Europe, we will include as many European countries as possible. Talking about Europe does not limit us to the European Union as such. We include other banks from Switzerland, Norway and Kazakhstan. Our focus remains on bank managers in different parts of

Europe, but our conclusions in the context of a general European view. Table 1.1 shows the characteristics that we deem most important, for each country separately. We based our sampling on these clusters, attempting to grasp as many different financial institutions as possible.

1.3.1.2 Data collection

Based on a detailed literature review and the comments of academics and practitioners, we built a survey that is used as a guideline during structured and semi-structured interviews with several banks in Europe. As we want to develop an in-depth understanding of how banks perceive the regulatory evolutions, interviews are the best way to go. In order to gather reliable information, we designed a questionnaire that gets the kind of information from which we can draw valid conclusions. More specifically, we have built the questionnaire to take into account that simple and precise questions increase response and decrease misinterpretation. On average an interview covered about 90 questions. Whenever possible the interviews were done face-to-face and were tape-recorded when authorized. This allowed us to observe as well as listen; it permitted more complex questions to be asked than in other types of data collection and it is an effective method of gathering data when the questionnaire is lengthy (Hollwitz and Wilson, 1993). However, as is true for all qualitative research designs, the outcome is more subjective by nature and we can never avoid that some bias - induced both by the participant and the interviewer - will enter the results. Furthermore also the sample selection of banks and interviewees might create a bias. As such, we should be aware of the drawbacks of this research method and be careful when interpreting the results.

Eventually, we interviewed several chief risk officers and/or Basel II responsibles throughout Europe. Data collection was done in 2 waves. The first interviews with 12 European banks were conducted in the first half of 2008, after Basel II implementation and at the point when the euro zone was entering a recession. In a second step, 36 interviews were conducted in mid 2010, in the aftermath of the financial crisis and before the BIS September 2010 meeting. We will report the results together, however when we notice a trend in the answers between 2008 and 2010 we will elaborate on it.

Our final sample includes 45 different banks covering 15 countries[13]. As described above, the banking institutions are split up primarily by country. Subsequently we will split them, within the country, according to their key differentiating characteristics. Often factors such as rating, size and type play a major role; however we see that the primary business activity, along with the type of bank, is the most comparable differentiator in almost all countries. When doing cross-tabulations, we will always keep an eye on the other factors and we will mention them wherever appropriate. For an overview of the

[13] In the first phase, 12 different European banks were involved, in the second phase 36 banks were involved and of the latter 3 had been involved in the first step. As such 45 different banks in total have contributed.

number of banks per country we refer to Figure 1.2. For a more detailed description of the banks in our sample we refer to appendix 1.3.

1.4 Results[14]

It is not that straightforward to draw general conclusions from so many questions and answers. Yet it is useful for policy makers and banks themselves to understand where banks in Europe stand and what the general direction is in which to proceed. If relevant we will add more detailed statistics to the trends we observe.

The next paragraphs consist of an integrated analysis of the different bankers in our research. We will start by discussing some problematic issues linked to the risk department within banks. This issue surpasses the Basel Accords, but is an important factor when it comes to its success. In a next step we will discuss the evolutions in credit risk management, internal rating models and the differences and similarities between regulatory and economic capital. Finally we will discuss the expectations for the Basel III accord mainly looking at topics that are subject to continuous discussion, as well as for the years to come.

1.4.1 Risk Management

1.4.1.1 The organization of risk management

The role of the risk department in banks has come under the spotlight over the past few years and the attention for the topic was further enforced by the crisis. Various stakeholders agree that the functioning of the risk department within banks should be reviewed. Both opinion leaders and regulators agree that risk managers should be positioned at a higher level in the hierarchy and should receive more power. However, there is quite a divergence in opinions on how this should be achieved. An important aspect under discussion is the centralisation, including a straight reporting line from the risk department, versus the integration of risk management in the banks. The latter, also referred to as the "ratatouille vision", implies that there is close interaction at different levels within the bank, between the risk departments and the other departments. The successful realisation of this vision would however imply a major switch in the internal culture of many banks. Anglo-Saxon regulators and supervisors are quite supportive of this. They defined a regulatory philosophy that is much more liberal than the one in continental Europe. This liberalist philosophy believes that a too restrictive regulation, intervening in the internal organisation of banks, will have a negative impact on innovation

[14] All the information that is listed below is based on the interviews except when we explicitly mention a reference.

and the efficiency of banks. As such they prefer to leave banks free to choose their management structures, but also punish them when this does not result in the postulated risk positions.
The fact that risk officers do not necessarily reject a strengthened and thus more restrictive supervision is confirmed by the results of our survey. Over 70% of respondents also argue that the chief risk officer should be at least to some extent responsible for reporting to regulators, rather than the whole management. 20% agrees with the liberal view of the supervisors. The major argument against this philosophy is that it implies an effective supervision of the risks taken by banks, which is currently not in place. Furthermore, bankers believe that the perceived effect of a better risk function on global financial stability is not that high. Later in this paper it is shown that this expected to have a low to only moderate impact, also relative to other factors.

Linked to the discussion above is the question of whether risk officers should receive a bonus. The continental group of regulators and supervisors (R&S) and academics and opinion leaders (AOs) believes that regulation should intervene to ensure the right incentives for those managers, but the liberal group of R&S believe this kind of decisions should be left to the banks. Most bankers (70%) feel that a fair wage should suffice to do a job well and those in favour argue that a long term bonus is very important and that no decent alternative is available. It is clear that at the end, the market sets bankers' incentive systems. However, due to the fact that banks are able to take more risk than other types of companies, they will suffer more from market pressure. As such it has been suggested by R&S that the voting power of short term shareholders be limited and the power of shareholders who stay in the bank to realise a long term project be reinforced.

In the optimization of the bank risk departments, an important role is set aside for the supervisors. All bankers believe that enhancement of capabilities at that level is a necessity. Furthermore all saving banks in our sample are convinced that better supervision is required to limit the commercial banks in their attitude. It should be noted that the supervisors themselves point to diverse structural problems. Firstly there is a need for better coordination and exchange of information between countries. Secondly some supervisors believe they should be closer to the day-to-day management of the banks in order to understand them better. Thirdly they believe that the function of supervisor should be split from the function of customer protection.

1.4.1.2 Credit risk management

Besides the organisation of risk management, the Basel Committee aims to integrate more risks into the new regulation. Monitoring liquidity risk, underwriting and concentration risks, counterparty risk, stress testing, valuation practices and exposures to off-balance sheet activities are at the centre of the better risk management. However at the same time and in the eyes of many AOs and R&Ss Basel III still fails to address the risk weighting of assets in an appropriate way.

An important part of risk management will always concern the management of credit risk. Taking into account the recent macro-economic evolutions, the new regulatory framework and the relaxing of lending standards (e.g. Zingales (2008)) it is interesting to see how credit risk management has evolved over the past years. In this section we will look at whether banks have experienced an evolution in credit risk management over the past years and if so, which part they attribute to the Basel II accord.

With respect to the quality of credit risk management currently in place, over 80% of the banks feel it is satisfactory and 20% even state that it is really good. Slightly less than 20% of the banks interviewed stated that the credit risk management needed important improvements and one bank stated that the current credit risk management in place was really poor. Notwithstanding the fact that credit risk has become more complex (see Altman et al., 2000; Keys et al., 2008 etc.) over 90% of the investigated banks are convinced that the credit risk management in their bank has improved[15] over the past years either to a greater or lesser extent[16]. This applies to all universal and investment banks in our sample. This development has mainly concerned data analysis and risk measurement (e.g. credit scoring by including concentration risk and counterparty risk), effectively doing stress testing and better forecasting models. The change can be explained as a result of better knowledge of how to measure and manage credit risk as well as the fact that senior management has become increasingly aware of the need to manage risk. AOs believe this is the result of both the crisis and the new regulations.

This perception is interesting when combined with the findings of Zingales (2008) and Dell'Ariccia et al. (2008) that show deterioration in lending standards in the years preceding the crisis. This risk-taking behaviour is stimulated when the true economic risk is not reflected in capital regulation[17] resulting in adverse selection and regulatory capital arbitrage. Securitisation (and re-securitisation) is a way to address high risk exposures while keeping profit at a high level. These practices are confirmed by Keys et al. (2008) who show that loans that are more eligible for securitisation experienced a 20% higher probability of default. As a response to the current crisis, where collateralized debt obligations comprised of asset-backed securities - the so-called re-securitisations - are shown to be highly correlated with systemic risk, Basel II requires a higher capital charge. Furthermore, under Basel II liquidity lines extended to support asset-backed commercial paper (ABCP) conduits require higher capital requirements by eliminating the distinction between short-term and long-term liquidity facilities. On top of that the committee has also proposed for banks to obtain comprehensive

[15] The interviews revealed that the changes have taken place in several domains ranging from portfolio management, risk rating systems, quantitative models, capital adequacy calculations, more proactive credit risk management, credit culture, organisational structure, centralised risk information system to more model-based decisions in credit approval process.

[16] No bank indicated it had deteriorated, however about 10% of the interviewed banks indicated that there had been no change.

information about the underlying exposure characteristics of their externally-rated securitization positions. Failure to obtain such information would result in higher capital requirements. However as the Basel II framework fails to clearly define how supervisory authorities should evaluate risk transfer, it is highly possible that a significant level of regulatory capital arbitrage will continue to exist especially among different countries, which may ultimately damage the level playing field. The new Basel III framework is not directly addressing this issue either. It has been argued that the new Basel III rules for securitisation will make securitisation less attractive to banks as it will be more of a burden on capital and returns will be lower. However, it will be hard to avoid regulatory arbitrage when there are still so many differences with respect to approaches, deadlines, options and national discretions.

Van Hoose et al. (2007) investigated the role bank capital plays in the safety and soundness of the banking system and conclude that because the intellectual underpinnings of Basel II are not really strong, the impact of pillar 1 on financial stability is ambiguous. However it could be argued that the recent positive evolutions in credit risk management are a consequence of Basel II and therefore the new framework has an unambiguous positive impact on financial stability. As such, it is relevant to understand what is triggering the positive evolution and more specifically whether Basel II plays a role in this.

A first important trigger seems to be data quality. As was already predicted by Altman and Saunders (1998), significant improvements in data on historical defaults and loan returns allow banks to improve risk management. On top of this, 65% of the banks are convinced Basel II was a direct trigger whereas the others claim Basel II had nothing to do with it. Mainly the larger banks are convinced that the positive evolutions were not induced by the regulatory framework and would have taken place anyhow. However at the same time these banks are convinced Basel II has structured matters and sped them up. More specifically Basel II seems to have contributed in several ways. At first by encouraging data quality and data availability, two things that are key in risk management. Furthermore by making risk management more structured and harmonised and by changing risk culture. A number of banks stated that Basel II seems to guide business sense as it forces top management to become more aware of the importance of risk management. Even banks that have always been highly risk oriented are forced by Basel II to measure things in a more exact and consistent way.

The above shows Basel II has played a role in the evolution of credit risk management for all banks, albeit indirectly. This finding is also in line with the initial perception banks had with respect to Basel II. Besides the potential capital relief, most banks were convinced of the impact Basel II could have on

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[17] But also deposit insurance guarantees resulting in moral hazard.

risk management. More specifically, over 80% of the banks investigated feel that Basel II and its regulatory capital requirements have been useful to the internal risk practices and management approaches. And almost 95% of all bankers agree that the Basel II regulatory capital is a core or an additional feature for risk management (see Figure 1.3). The current crisis has underscored the importance of effective credit risk management as a key component to financial stability. As such Basel II has been important if not for the capital cushion as such, then for the impact on risk measurement and awareness in banks. Of course better risk management and measurement at the level of a bank do not necessarily result in a reduction of regulatory capital arbitrage or in a safer financial system, and as such we agree with Van Hoose (2007) that the net effect of Basel II on financial stability is ambiguous (see below).

The R&S and some of the AOs agree that Basel II had an added value when it comes to the internal risk management of banks. In that sense Basel II has certainly been a step forward and as such Basel II has been evaluated quite positively in that sense. As such, it is striking to see how again bankers hope that Basel III will not be implemented as proposed, and that a 73% majority expect the new regulation not to trigger changes in credit risk management.

1.4.2 Internal rating model

The evolution in credit risk management has had a positive impact on the use of internal models (Carey and Hrycay (2001), Altman et al. (2002), Saunders (2002), Van Gestel et al. (2009)). The next part gives an overview of rating model practices in the interviewed banks.

Internal models for measuring risk are used by 78% of our sample. In 90% of the cases it holds that large banks use internal models, whereas smaller banks use them only in 70% of the cases. Those that have an internal rating model are generally happy with their model (80%). The top risks (in addition to the regulatory model) measured by internal models are liquidity risk and counterparty risk. In Figure 1.4, you can find the risks measured by our sample of European banks.

Insert Figure 1.4 here

When building a credit risk model, a bank has to decide on the rating philosophy. The time horizon for assessing the creditworthiness of borrowers in assigning ratings - which is part of the rating philosophy - is on a spectrum between point-in-time (PIT) and through-the-cycle (TTC)[18]. Even

[18] Point-in-time (PIT): the rating gives an indication of the borrower's current condition and/or most likely condition over a short chosen time horizon, typically one year.

though this is an arbitrary distinction, the chosen rating philosophy influences many aspects ranging from pricing, credit and portfolio monitoring to level and volatility of capital requirements and as such has an important impact on both financial stability and the level playing field. If the PD assigned to a rating grade is fixed, a TTC rating system will result in relatively stable regulatory capital requirements, whereas a PIT system will produce more counter-cyclical capital requirements. As such, in order to reduce the incentive for regulatory capital arbitrage it is important that the rating philosophy is consistently applied in both regulatory and economic capital. Some opinion leaders have argued that the remedy for pro-cyclicality in the Basel II capital requirements is the use of TTC estimates for the probability of defaults and recovery rates. On the other hand this would also introduce unacceptable vagueness into the estimates and seriously undermine the basis for backtesting and verification (Rowe, 2003).

It could be expected that financial institutions chose more often for the PIT method, because it is less complex (Treacy et al. 2001, Rikkers and Thibeault, 2007). This is in line with our findings, where at this point, most banks are still using the PIT approach that is consistently applied across asset classes. For the future, there is a clear tendency towards the TTC rating philosophy. An important reason why banks opt for a certain rating philosophy seems to be pragmatism and data availability, but also credit culture and competition. Furthermore some banks also admitted that the rating philosophy was coincidence rather than a well balanced choice and that it was partly inspired by rating agencies and supervisors. Everyone agreed there is no model that is completely PIT or TTC and as such they are convinced that some surfing through the cycle is unavoidable. Besides the difference in rating philosophy, the number of rating classes also differs significantly between European banks, ranging from 7 to 23. This difference in granularity between banks is mainly induced by the differences in portfolio and models in use. Internal rating systems with many grades are more expensive but especially for profitability analysis fine-grained distinctions are necessary to support risk-return trade-offs. Even though there is a large difference in granularity, all banks are convinced that there is a large homogeneity in each rating class of the bank's internal rating system.

It is important to note that some banks use different rating philosophies depending on the purpose of the rating. For instance one bank uses PIT for pricing and impairment and TTC for capital calculations. This practice could be an additional stimulus for capital arbitrage.

After developing an idea on the way risk management and credit risk management has evolved, we will now elaborate on the way regulatory and economic capital are being calculated and how this differs across banks.

Through-the-cycle (TTC): the ratings give an indication on the borrower's creditworthiness, based on a full business or economic cycle.

1.4.3 Regulatory and economic capital

1.4.3.1 Regulatory capital

As was already mentioned, over 90% of the banks questioned view regulatory capital as a core or at least an additional feature in risk management (see Figure 1.3). Besides compliance, it is primarily used for the measurement and management of risk (78%), external reporting (64%), and the strategic use and optimal allocation of capital (53%). With respect to credit risk, we see that 75% of banks currently use the standardised approach and one fifth use the advanced internal rating based approach. In line with expectations, big banks in particular use the advanced approach (AIRB), which has important implications with respect to the level playing field objective of the accord.

Insert Figure 1.5 here

Insert Figure 1.6 here

One third of the respondents, mainly investment or private banks, claim they will still use the standardised approach in the future. We received many reasons why banks would not apply for the AIRB. In order of frequency the top reasons are: the complexity of IRB, the business model of the bank, the implementation period and a lack of resources. Other less frequently cited reasons are lack of available data, lack of belief in the concept, limited interest and the fact that government puts more emphasis on the standardised approach. For banks that do not adopt the IRB approach, about half of them believe their competitive position will be affected. The reasons for this are diverse, but the fact that the competitor will have a better view of the risk/return relationship is the most frequently cited reason (30%).

In future, clearly more banks are planning to adopt the IRB approach. An important reason for this finding is the better competitive position that is induced by the IRB approach. Depending on portfolio risk, advanced IRB could result in the highest capital relief, freeing up resources that can be used for other purposes. However, most banks indicated that the main advantage of IRB is the fact that it enables banks to have a better understanding of the relationship between risk and return. As a second and third advantage, banks indicated a better understanding of risk concentration and more complete and timely risk data. This again confirms that the main issue in capital regulation is not necessarily the ultimate capital level but rather the impact it has on risk management practices. These findings could also positively contribute to regulatory capital arbitrage as the IRB approach can be regarded as a compromise between a purely regulatory measure of credit risk and a fully internal model based approach and as such might result in a high convergence between regulatory and economic capital.

Hybrid: the rating is in the area between PIT and TTC.

In the context of the crisis, R&S and AOs increasingly formulated their opinion in this respect. AOs in favour of the use of a standardised model argue that the advanced model is too opaque to implement and sometimes not well understood by bankers. Furthermore, they claim it is a naive perception to believe that such models incorporate all kinds of risk and they express their worries about the underlying assumption of the model, such as the unrealistic normal distribution. As a result, they feel that bankers should employ simpler and more traditional systems in their credit risk management. Complexity can result in systemic risk or information asymmetry. An important issue here is that the models are too complex for effective supervision. Others argue that banks should use advanced models because they help them to better quantify risk and are more suitable for complex bank activities. The idea is that there is no necessary trade-off between accuracy and transparency of the models. This is supported by 70% of the banks who apply an internal model.

Ultimately both types of models are criticised. They fail to include tail risk and models are never a reflection of reality. This explains the failure of both approaches during the crisis. From the opinion of R&S and AOs it is thus not clear which model should be preferred. Bankers move towards an advanced model, but is not clear that they do so because they really believe the model is better or because it enables them to hold less capital requirements. What is clear is that the choice of the model depends greatly on the size, business model and activities of the bank.

1.4.3.2 Bank capital buffers

In reality, only a small fraction of the banking system is constrained by regulatory capital requirements. This does however not imply that capital requirements do not matter (Repullo and Suarez, 2010). Banks seem to anticipate that shocks to their earnings and the macro-economic environment weaken their capacity to lend in the future and, as a safety measure, hold capital buffers. Moreover, during the latest financial crisis, banks encountered the financial shocks with capital cushions significantly above regulatory thresholds. However, partly due to pro-cyclical behaviour, the overall cushion seemed too thin. A big challenge for banks is the way they deal with uncertainty about the scale of losses they can face in a less benign economic and financial environment, and the size of the cushion they have to build against that uncertainty. Risk management tools also rely on history and experience which makes it very difficult to assess potential future losses for innovative financial instruments or unseen financial shocks.

Likewise in our sample all banks hold capital well above the required minimum. It is difficult to empirically distinguish different underlying determinants of bank capital buffers (e.g. Allen et al., 2009). Banks may build up capital stocks more than they currently need if they fear future costs or uncertainties in case they would need to raise capital (Berger et al., 2008). As such, differences can be induced by differences in access to funding, shareholder structure, portfolio risk etc. (Jokipii, 2008). Due to the diversification effect, economies of scale in screening and the ‘too big to fail’ principle, larger banks are expected to hold smaller average capital buffers. However, we find no evidence for this in our sample. Banks listed several reasons why they hold excess capital. Forty percent explain the buffer by the fact that Basel II fails to recognize certain risks, 25% says it is to avoid supervisory intervention and another 16% holds a buffer with the direct purpose of improving the bank's rating. Another frequently cited reason for smaller banks is that it is necessary to have this buffer to convince their clients of good solvency. Another argument was that 8% is just not enough; business cycles require the capital base to be higher so that it could protect banks better during a crisis. One bank stated they used economic capital to decide on the capital buffer. In the context of the crisis and regulation, the R&S and AOs agree that higher capital requirements are needed, but at the same time acknowledge that this could not have prevented the crisis. The idea of countercyclical capital buffers is widely supported as it works both as a buffer and as a way to limit the asset bubbles.

Where Basel II has proven its strengths when it comes to risk management, in preventing downturns, the capital requirements under Basel II are considered less useful. After all that has been said and done, thirty percent of the people investigated still believe that the current crisis would have hit less hard if Basel II had already been implemented. However the majority of the respondents feel that the loopholes (liquidity risk, securitisation, pro-cyclicality etc.), the scope and the room for interpretation are too big to make the regulatory framework successful. R&S and AOs also recognise the limits of Basel II. The accord did not look comprehensively at risk, the relationships and correlations between different types of risk are not taken into account, off balance sheet items were not covered, capital buffers were too thin, cyclicality was enhanced and the models not well understood. Knowing this, another question that should be addressed is the extent to which the ultimate goal of Basel II, further alignment between regulatory and economic capital, has been achieved.

1.4.3.3 Economic capital

Economic capital can be defined in various ways. One bank defined it as the positive difference between available risk coverage capital and required risk capital. However, in reality, economic capital should not always exceed regulatory capital. Many banks tend to define it as "an add-on buffer (covering other risks) on pillar 1 capital". In our sample, over 70% of banks currently calculate economic capital and in the future over 80% will calculate it. In a number of banks it was introduced in the early nineties, however in most cases it was introduced only very recently. Non-rated or low-rated banks in particular frequently do not calculate economic capital. The banks that are A-rated or above, almost all calculate economic capital. Big banks also do so more often than small banks and this will be even more the case in the future. In a few banks it has gained considerable acceptance over the past years, in others it is still in its infancy or not yet part of their strategy. The confidence interval for economic capital ranges from 99.9 (Basel II pillar 1) to 99.98. The economic capital model itself differs a lot across banks. About 40% of the banks use a default model where the other 60% rely on a market value model. For most banks MKMV is a fundamental input. No bank uses a reduced form approach for its economic capital calculations. The biggest difference across banks lies in the parameters that are included in their economic capital calculations. Besides the regulatory ingredients credit, market and operational risk, only a few banks include interest rate, business, reputational risk etc. in economic capital as well. One bank stated that they try to capture all risks they are confronted with and those risks that are difficult to quantify are covered by an arbitrary buffer. Furthermore, less than 50% of the banks explicitly recognise concentration risk at this point. The above clearly shows that where banks tend to converge with respect to regulatory capital practices, there are still big differences across banks with respect to economic capital calculations.

1.4.3.4 Difference between regulatory and economic capital

Jones (2000) pointed out that the underlying factors driving regulatory capital arbitrage will continue to exist unless economic and regulatory measures of risk converge. Diversification and concentration effects create the biggest gap between economic and regulatory capital. The above shows that current practice with respect to economic capital calculations is still not up to its full potential, which could imply that in the future due to better correlation and concentration measurement, the gap between regulatory and economic capital could increase even further. Also differences in the PD, LGD and EAD parameters play an important role in the divergence between the two capital numbers.

For non-rated banks, the difference between economic and regulatory capital is often higher than 20%. Whether this difference is positive or negative, is less clear. Half of the banks have a higher economic capital and the other half a higher regulatory capital. When we compare the two levels of capital in terms of changes over time, we see that half of the bankers claim that there has been a shift in both capital numbers, due to a change in credit risk exposure, interest rate and business risk, growth of the business and changes of economic conditions. Those that expect a shift in the capital level attribute it to the new Basel III framework.

What is important to understand is that for 50% of banks economic capital is still below regulatory capital. Taking into account that regulatory capital arbitrage is widely perceived as a “safety valve” for reducing the adverse effects of regulatory capital requirements that exceed levels commensurate with the bank’s underlying economic risk, this implies that incentives for RCA will continue to exist.

At the same time most banks acknowledge that economic capital is currently not used to its full potential, and that it often has the same use as regulatory capital. More specifically, at this point economic capital is not used for performance measurement or as a driver for compensation. On the contrary it is used for Basel II pillar 2, measurement and management of risk and risk adjusted pricing and this use is expected to increase.

With respect to loan pricing, 38% currently use economic capital. The others use other methods such as customer pooling, competitive market rates or regulatory capital (sometimes with a buffer). Credit decisions will always depend on the expected yield over a minimum margin where credits priced below the minimum margin are not profitable and will not be supplied. Taking into account the more conservative features of regulatory capital, one could argue that regulatory capital is too expensive and that economic capital is a more valid input for pricing. In reality most of the interviewed banks still rely on regulatory capital for loan pricing. However there is a tendency that in the near future, 60% of banks will rely more on economic capital or on a combination of both.

The above clearly shows that current practices differ a lot across banks especially with respect to economic capital. The fact that banks seem to move in the same direction for regulatory capital could imply that Basel II is indeed increasing the level playing field. However for economic capital practices there is still a long way to go. In the absence of greater convergence, regulatory capital standards seem destined to become increasingly distorted due to further financial innovations and improved and new methods for economic capital calculations and RCA. So even though Basel II has a positive impact on risk management practices, the impact on regulatory capital arbitrage and associated financial stability is ambiguous and will highly depend on the financial institutions, which in itself will again distort the level playing field. Furthermore, under Basel III banks will also weasel their way out of its strictness, by modifying the risk weights in their favour. Banks will figure out what sorts of regulatory capital arbitrage they can do. This again stresses the importance of bank supervision.

1.4.4 Basel III[19]

1.4.4.1 The perception of Basel III

At this moment the foundations of Basel III are being laid. Most financial institutions believe there is a need for new regulation, with 64% agreeing that this should be at least on a European level and 76% agreeing that preferably there should be a global regulation (see Figure 1.7). Hence global regulation is the most vital requirement. This is supported by both R&S and AOs. A general fear of not regulating other continents such as America, where the crisis originated, is bigger than the fear of not regulating the European Union. Furthermore, bankers believe that the new regulation should be as strict as the current one and preferably even stricter. All types, sizes, rated and unrated banks agree on this matter.

[19] These questions were only addressed during the second wave of interviews.

Insert Figure 1.7 here

When asking bankers about the ideas behind the new banking regulation, many admitted that they did not really know the proposal in depth. The lack of Basel III awareness is quite striking and logical at the same time. In the next paragraphs we will look at the extent to which certain ideas, including new proposals of the Basel Committee, will have an impact on banks and financial stability in general.

First we will address the factors that ought to impact the banks. More specifically we asked bankers to what extent they felt that their bank would be impacted by the new rules. The answers are depicted in Figure 1.8.

Insert Figure 1.8 here

As can be seen, banks expect the impact of the Net Stable Funding Ratio to be highest. This is followed by the changes in accounting standards[20], the liquidity risk, the leverage ratio and the countercyclical capital buffer. Banks do not really seem to worry about the new definition of capital. Our results also show that the impact is expected to be higher for retail banks and universal banks compared to investment and private banks. With respect to the operational impact of Basel III, banks expect the highest impact on reporting and the risk function as such.

Next we look at the perceived effect on global financial stability. Generally speaking, bankers think that financial stability will be enhanced mostly by a reinforced role of the supervisors. Contrary to what could be expected, banks are really fine with having stricter supervision, as they believe that fair competition will suffer otherwise. Bankers believe that the least effect on financial stability would come from a review of the CRO function. In the figure below you can see to what extent there is an expected impact for certain factors.

Insert Figure 1.9 here

On 16 December 2010, the Basel Committee released the results of the comprehensive quantitative impact study (QIS), in which they assess the impact of capital adequacy standards announced in July 2009 and the Basel III capital and liquidity proposals published in December 2009. The estimates presented assume full implementation of the final Basel III package, based on data as of year-end

[20] National and international regulators are currently reviewing the rules and are divided between more fair value or more losses and volatility for banks. Discussing the accounting standards is beyond the scope of this paper; however it is interesting to see that banks believe that they will be highly impacted by accounting rules. This is in line with our finding that 84% of the banks state that as IFRS enhanced cyclicality, it has reinforced the crisis.

2009. The BIS concludes that in order to prevent another global financial crisis, banks across the world will need to raise nearly €600 billion in extra capital as a result of the new rules. This number does not take into account the extra capital charges that are likely to be imposed on systematically important banks, which are deemed too big to fail. The most important findings of this QIS are listed below.

Including the effect of all changes to the definition of capital and risk-weighted assets, as well as assuming full implementation as of 31 December 2009, the average common equity Tier 1 capital ratio (CET1) of Group 1 banks[21] was 5.7%, as compared with the new minimum requirement of 4.5%. For Group 2 banks[22] the average CET1 ratio is 7.8%. In order for all Group 1 banks in the sample to meet the new 4.5% CET1 ratio, the additional capital needed is estimated to be €165 billion. For Group 2 banks, the amount is €8 billion. Including both the 4.5% minimum requirement and the 2.5% capital conservation buffer, the Committee estimated that Group 1 banks in aggregate had a shortfall of €577 billion at the end of 2009 and Group 2 banks would have required an additional €25 billion. As a result of the new definitions of capital, the Tier 1 capital ratios of Group 1 banks would on average decline from 10.5% to 6.3%, while total capital ratios would decline from 14.0% to 8.4%. For Group 2 banks, Tier 1 capital ratios would decline from 9.8% to 8.1% and total capital ratios would decline from 12.8% to 10.3%. Furthermore, the overall risk-weighted assets would increase by 23.0% for Group 1 banks, mainly driven by charges against counterparty credit risk and trading book exposures. As a result the risk-weighted assets of Group 2 banks would increase by an average of just 4.0%. It is clear that the changes in risk-weighted assets have less impact on banks' capital positions than changes to the definition of capital. Interesting to see is that the latter was feared less by the banks in our sample. The new liquidity standards result in an average LCR and NSFR of 83% and 93% respectively for Group 1 banks and 98% and 103% for Group 2 banks. Banks have until 2015 to meet the LCR criterion and until 2019 to meet the NSFR standard. Finally, the weighted average leverage ratio using the new definition of Tier 1 capital is 2.8% for Group 1 banks and 3.8% for Group 2 banks.

The Chairman of the Basel Committee concludes that the Basel III rules will gradually increase the level of high-quality capital and liquidity buffers in the banking sector. Furthermore, he stresses that the transition period, which has been ignored in the QIS, should allow banks to move to the new standards in a manner that does not jeopardize a sound economic recovery. However, we feel it is important to keep in mind that the averages listed above could mask some worrying shortfalls at individual bank level and that some sources of concern are therefore not identified at this stage.

R&S and AOs believe that Basel III should look more comprehensively at the risks, meaning that risks should no longer be looked at in an isolated way and that it should cover all risks and off-balance sheet

[21]Group 1 banks have Tier 1 capital in excess of €3 billion.

items. New financial instruments should be investigated more and the loopholes should be tightened. The fear for the new regulations by bankers is confirmed by all parties; however, this has been tempered by the fact that the new rules will be implemented step by step over a long time horizon. Furthermore R&S and AOs believe that stress testing should be integrated into the risk models of banks and these models should account for interconnection between banks and should incorporate correlation between risks.

Of the banks that were more familiar with the Basel III framework, about half of them are convinced that Basel III will succeed in reducing pro-cyclicality. Those who do not believe this argue that regulation will always lag behind the market and that this is an intrinsic error in the system.

1.4.4.2 Basel III and the level playing field

One of the goals of the Basel Committee is the realisation of an international compromise on regulation in the financial sector. This is intended to create a level playing field and free market for institutions all over the world. The question remains however whether it is realistic and necessary to include every country and every type of bank in the new regulation. 71% of all banks believe that the new regulation should be applicable to all banks without any exception. Of the big banks, as many as 90% agree. The smaller banks and the savings and cooperative banks tend more towards an unlevel playing field. The banks that are in favour of a split regulation, consider the factors size and activities as prime determinants. Continental R&S agree that a common global regulation is the ultimate way to proceed. They believe that there are many positive intentions to create a common regulation in the context of the G20 for international solvency rules. At the same time they realise that these negotiations will be difficult and not all supervisors will be able to apply the regulations on all their banks. Their hope is that it will be possible to apply these regulations at least to all international banks.

When it comes to the discrimination between big and small banks, the AOs remain cautious. They argue that the regulation should apply to all type of banks without any differentiating factor. The smaller and less risky banks should realise that eventually this will be beneficial to the economy as a whole. This vision is opposed by the argument that there should be some differentiating factors, for example risk profile and size as proxies for potential systemic risk of the bank. Furthermore, most agree that eventually the level playing field should be established at international level, but that probably some local changes will be necessary first to allow it to happen. Bankers themselves do not really believe that a level playing field will ever be achieved.

[22] Group 2 banks don't have Tier 1 capital in excess of €3 billion.

With respect to the way supervision should be organised, most R&S believe in a coordination of supervision rather than in a centralised supervision. This is primarily because Europe lacks financial resources if something were to go wrong. Furthermore, national supervisors benefit from proximity. Only a minority of regulators feel that Europe has sufficient resources and that full responsibility is therefore the only way for effective cross boarded supervision. For banks it is less clear how this should be organised. However there is a tendency for supervision within the EMU-zone, a dual supervision or even a global one for international banks. This is especially the case as some of the banks' subsidiaries suffer from the conflict of differing regulations in the country where the headquarters are established.

1.5 The road towards financial stability: beyond Basel III

The financial crisis resulted in a deep shock for the financial sector and for society as a whole. But every crisis also creates opportunities. This study proves that bankers, R&S and AOs believe there should be some major changes in the regulations of the financial sector. This means there is a unique chance for regulators and politicians to create a regulation that ensures more financial stability and guarantees more welfare for the whole society.

Next to the Basel reforms, there are quite some voices to increase the regulation of credit rating agencies (CRAs), reduce the pro-cyclicality of international accounting standards (IFRS) and further regulate the corporate governance at banks. A new regulation on those three subjects is supported by the banks. The top issues for banks, in favour of regulation of CRAs, are the fact that they have too much influence, that they are not held responsible for misleading information and that conflicts of interests with issuer-paid research should be avoided. For the banks that do not belief in rating agency regulation, the argument is that they would become less effective if the open market would be given up. Continental R&S believe there should be more regulation, more transparency that is guaranteed by the government and they stress that the government should further work on the conflicts of interest. The Anglo-Saxon vision is slightly different; they argue that credit rating agencies are deemed an instrument of the market and should thus respond to the demand of the market.
Several AOs emphasized the importance of validating the model employed by the CRAs which should be done by supervisors. Moreover, they argue that there should be a standardized model used by the CRAs. The main objective behind this idea is to make the ratings more comparable. Furthermore, it can be expected that more transparent models will result in fewer mistakes. Another solution suggested in the US is an increased competition between rating agencies. However, the effectiveness of all these propositions still needs to be proved.

After the crisis, also international accounting standards (IFRS) came under attack. An overwhelming majority of 84% of the bankers states that, because the accounting method enhanced cyclicality, it reinforced the crisis. Several changes on IFRS are therefore advised by bank managers (e.g. not altering IFRS standards this frequently etc.). AOs believe IFRS is still the best way of accounting. However they claim that the International Accounting Standard Board (IASB) should pursue a thorough review of the concept and its pro-cyclical impact. Again one could differentiate between an Anglo-Saxon vision and a continental vision of the R&S. The first one states that IFRS did not make the crisis worse and that the cyclicality of accounting is just a symptom, rather than the cause. Regulators on the continent agree that financial reporting is about communication to the market. However, some believe that IFRS has proven not to be the best way of communication. The value changes are no tangible profits, what makes the interpretation of the numbers very hard, even for experienced analysts. Some regulators argue that the trading book can be booked consistently at fair value, but not the banking book. Other regulators warn for the fact that banks will be able to play with this difference and that to avoid this, one system is preferable, probably fair value. There is thus a lot of critique on IFRS. However at this point, there are no practical propositions on how to change it.

Finally, when it comes to the regulation of the risk department, the regulator is highly dependent on the goodwill of the bank managers and shareholders to apply an effective regulation. It is clear that the crisis resulted in an increased importance of risk management in banks. But even the introduction of a direct line between risk management and the board of directors does not guarantee that there will be more attention for the risk management division in the long term. Because banks are too big and too important to fail, and shareholders are sometimes only bound to the company for a very short time, they have an incentive for excessive risk taking. This is why there were some propositions on the reintroduction of Glass-Steagall (tackling the problem of too important to fail), limiting the size of the banks (tackling the problem of too big to fail) and limiting the voting rights of short term shareholders. At the level of the banks, a reintroduction of Glass-Steagall could count on some support, but not from the universal banks. Many R&S and AOs believe Glass-Steagall and limiting the size of banks will result in unprofitable financial institutions. Another problem with those suggestions is that it should be applied in the whole world in order to create a level playing field. The proposition on the incentives of the shareholders therefore probably has the best chance of being realized.

1.6. Conclusion

Traditionally, capital requirements have been the foundation of bank regulation. However, their effect on bank behaviour and financial stability is highly contested. In addition to the regulatory requirements, financial institutions calculate their own economic capital reflecting the unexpected losses and true risk according to the specific characteristics of their portfolio. The ultimate goal of the

Basel II framework is the convergence between both capital numbers to further promote financial stability. However, the Basel II' focus on making prudential capital more closely aligned to the banks' own economic capital could not offset the latest implosion of the financial system. Basel II, to all intents and purposes, never properly came into effect and it became clear that pre-crisis capital standards were too weak for the types of risk that emerged. As a consequence, the Basel Committee is now working on a new accord usually referred to as Basel III, whose ultimate goal is to fundamentally strengthen global capital standards. The question of course remains whether the suggested changes will address the gaps in Basel II in a sufficient and accurate way.

In this chapter we look at whether and how European banks adjust their behaviour in line with the regulatory framework. More specifically, based on several interviews with different bank stakeholders, we develop an understanding of current practices with respect to risk management, internal rating models, regulatory and economic capital, Basel II implementation and Basel III expectations. In doing so, we are addressing another objective of the Basel accords, the creation of a level playing field.

Based on our interviews it is clear that Basel II has been a first step in the right direction. Basically all parties agree that it has played an important role in the evolution of risk management, mainly by the introduction of internal models and pillar 2 economic capital. European banks seem to move in the same direction for regulatory capital, however for economic capital practices there is still a long way to go and the room for regulatory capital arbitrage remains to exist. Where Basel II has proven its strengths when it comes to risk management, in preventing downturns, the capital requirements under Basel II are considered less useful. The majority of the respondents feel that the loopholes, the scope and the room for interpretation are too big to make the Basel II regulatory framework successful.

As a result all parties agree that a new regulation is necessary, however there is quite some disagreement on how this should be done. There has been a huge flow of writings and suggestions on what the new financial regulation should look like. Some believe it should be more risk sensitive, based on the business model of the banks, while others believe that some general rules are preferable. The regulation could be liberal or more restrictive, applied on an international level or on a regional and national level. The choice made should consider some limitations, however. The new regulation should be practical, meaning that it should be possible for supervisors to control it effectively and for all banks to apply it with relative ease. The political limitations should be considered and one needs to make sure that its impact on the total welfare is optimized. Finally, the new regulation should also be acceptable for the majority of the banks, taking into account their differences in activities, ownership structure, size etc.

It has been suggested that Basel II did not include sufficient capital requirements. Banks believe that regulatory capital should be increased but only in a limited way. Regulators and supervisors (R&S) and academics and opinion leaders (AOs) warn of the negative effects higher capital requirements could have on an already damaged economy. This is why capital requirements should be introduced in the long term. Furthermore R&S and AOs state that higher capital requirements will never be sufficient when another financial crisis comes. Therefore it is seen as one of many changes in the new regulation. The advantage of higher capital requirements is that it works on two levels: it creates a buffer and on a macro-economic level it limits the creation of asset bubbles.

European bankers are mainly afraid of the impact of the net stable funding ratio and the new accounting rules and stress the importance of a reinforced role of the supervisors. Banks believe that reinforcement and the realization of effective supervision is the main criterion for the realization of a more stable financial market. This confirms the important role our research assigns to the supervisor and the importance of this practical regulation. One of the major difficulties will be to make a reliable estimate on how far the capabilities of supervisors go. Another difficulty on the subject of supervision is that it is still a national responsibility that will not be centralised very quickly for political reasons. A solution for this is a European coordination of supervision, the so called level two supervision and an increased communication and cooperation between supervisors.

R&S and AOs believe that Basel III entails a lot of improvement, but they argue that Basel III should look more comprehensively at the risks. We agree that one of the main weaknesses in Basel III is still the risk weighting of assets, which is inherently backward-looking and easy to game. The fact that banks will need to hold much more common equity than before, will probably increase the incentive to find low-risk-weight assets which can be leveraged much more than risky assets. Furthermore banks will be incentivised to increase returns without increasing measurable risk and thus will further push risk in the tails. We believe that in the absence of greater convergence between regulatory capital and true risk, regulatory capital standards seem destined to become increasingly distorted due to further financial innovations and improved and new methods for economic capital calculations and regulatory capital arbitrage. Also under Basel III banks are expected to weasel their way out of its strictness, by modifying the risk weights in their favour. Banks will figure out what sorts of regulatory capital arbitrage they can do. The question of course remains whether some Basel Accord could ever really avoid this, but it’s important to keep in mind and it again stresses the crucial role of bank supervision.

We can never expect a regulation to prevent all banking crises in future, and anything which reduces its likelihood is a good thing. Our research shows that financial stability cannot be realized by one single measure, or in one single day. It will take time and will consist of many different regulations, as a result of a compromise between regulators, politicians and bankers.

1.7 References

Alexander C., Sheedy E. 2008. Developing a stress testing framework based on market risk models. Journal of Banking & Finance 32, 2220-2236.

Allen L., DeLong G, Saunders A., 2004. Issues in the credit risk modelling of retail markets. Journal of Banking & Finance 28, 727-752.

Allen F., Carletti E., Marquez R., 2009. Credit market competition and capital regulation. Review of Financial Studies, forthcoming.

Altman E., Saunders A., 1998. Credit risk measurement: developments over the last 20 years. Journal of Banking & Finance 21, 1721-1742.

Altman E., Suggitt H., 2000. Default rates in the syndicated bank loan market: a mortality analysis. Journal of Banking & Finance 24, 229-253.

Altman, E., S. Bharath, Saunders A., 2002. Credit ratings and the BIS capital adequacy reform agenda. Journal of Banking & Finance 26, 909–921.

Araten M., 2006. Economic versus regulatory capital. RMA Journal 88, 42-48.

Avery R.B, Berger A.N., 1991. Risk-based capital and deposit insurance reform. Journal of Banking and Finance 15, 847-874.

Ayadi R., Schmidt R.,Valverde S., 2009. Investigating diversity in the banking sector in Europe. The performance and role of savings Banks. Brussels: CEPS.

Barth J.R., Brunmgaugh R.D., Wilcox J.A., 2000. The repeal of Glass - Steagall and the advent of broad banking. Journal of Economic Perspectives 14, 191-204.

Barth J.R., Caprio G., Levine R., 2001. The regulation and supervision of banks around the world: a new database. University of Minnesota Financial Studies Working Paper No. 0006; World Bank Policy Research Working Paper No. 2588 , 92.

Barth J.R., Gerad C., Levine R., 2008, Bank regulations are changing: For better of worse? Comparative Economic Studies 50, 537-563.

Barth J.R., Lin C., Ma Y., Seade J., Song F.M., 2010. Do bank regulation, supervision and monitoring enhance or impede bank efficiency? Working Paper.

Basel Committee on Banking Supervision (BCBS), 2006. International convergence of capital measurement and capital standards. http://www.bis.org/publ/bcbs107.pdf

Basel Committee on Banking Supervision (BCBS), 2006. Results of the fifth quantitative impact study (QIS 5). http://www.bis.org/bcbs/qis/qis5.htm

Basel Committee on Banking Supervision (BCBS), 2008. Range of practices and issues in economic capital modelling. http://www.bis.org/publ/bcbs143.pdf?noframes=1

Berger A.N., Richard J., Giorgio P. Szego, 1995. The role of capital in financial institutions. Journal of Banking & Finance 19, 393-430.

Berger A., Deyoung R., Flannery M., Lee D., Öztekin O., 2008. How do large banking organizations manage their capital ratios? Journal of Financial Services Research 34, 123-149.

Benston G.J., Kaufman G., 1996. The appropriate role of bank regulation. The Economic Journal 106, 688-697.

Brunnermeier M., Crochet A., Goodhart C., Persaud A.D., Shin H., 2009. The fundamental principles of financial regulation. Geneva Reports on the World Economy 11, ICMB and CEPR.

Blum Jurg, 1999. Do capital adequacy requirements reduce risk in banking? Journal of Banking & Finance 23, 755-771.

Brewer E., Kaufman G.G., Wall L.D., 2008. Bank capital Ratios across countries: why do they vary? Journal of Financial Services Research 34, 177-201.

Burns R.L., 2005. Economic capital and the assessment of capital adequacy. RMA Journal 87, 54-62.

Carey M., 2000. Dimensions of credit risk and their relationship to economic capital requirements. In Mishkin, Frederic S. (Ed.), Prudential supervision: what works and what doesn't. NBER and UC Press.

Carey M., Hrycay M. 2001. Parameterizing credit risk models with rating data. Journal of Banking & Finance 25, 195-270.

Carey M., Stulz R.M., 2005. The risks of financial institutions. NBER working paper No. 11442.

Cole R.A., Gunther J.W., 1995. Separating the likelihood and timing of bank failure. Journal of Banking & Finance 19, 1073-1089.

Crouhy M., Galaib D., Marka R., 2000. A comparative analysis of current credit risk models. Journal of Banking & Finance 24, 59-117.

Dell'Ariccia G., Deniz I., Laeven L., 2008. Credit booms and lending standards: evidence from the subprime mortgage market. CEPR Discussion Papers 6683.

Diamond D., Dybvig, P., 1983. Bank runs, deposit insurance and liquidity. Journal of Political Economy 91, 401-419.

Diamond D., 1984. Financial intermediation and delegated monitoring. Review of Economic Studies 51, 393-414.

Diamond D., Rajan G., 2000. A theory of bank capital. Journal of Finance 55, 2431-2465.

Dietrich J. Kimball, James, C., 1983. Regulation and the determination of bank capital change: A note. Journal of Finance 38, 1651-1659.

Dietsch M., Petey, J., 2004. Should SME exposures be treated as retail or corporate exposures? A comparative analysis of default probabilities and asset correlations in French and German SMEs. Journal of Banking & Finance 28, 773-778.

Dowd, K., 1999. Does asymmetric information justify bank capital adequacy regulation? Cato Journal 19, 39-47.

Dowd, K., 2000. Bank capital adequacy versus deposit insurance. Journal of Financial Service Research 17, 7-15.

Elizalde A., Repullo R., 2007. Economic capital and regulatory capital in banking: what is the difference? International Journal of Central Banking 3, 87-117.

European Central Bank, 2009. EU Banking sector stability.

Flannery M.L., Rangan K.P., 2002. Market forces at work in banking industry: evidence from the capital build-up of the 1990s.Working Paper.

Furlong F.T., Keeley M.C., 1989. Capital regulation and bank risk-taking: a note. Journal of Banking & Finance 12, 883-891.

Gennotte G., Pyle D., 1991. Capital controls and bank risk. Journal of Banking and Finance 15, 805-824.

Gordy M., 2003. A risk-factor model foundation for ratings-based bank capital rules. Journal of Financial Intermediation 12, 199-232.

Gordy M., Howells B., 2004. Procyclicality in Basel II: can we treat the disease without killing the patient? Federal Reserve Board.

Griffith-Jones S., 2003. How to prevent the New Basel Capital Accord Harming Developing Countries. Paper presented at the WADMO Conference/ General Assembly jointly with UNCTAD in Geneva, November.

Gropp R., Heider F., 2010. The determinants of bank capital structure. Review of Finance 14, 587-622.

Hellmann T.F., Murdock K.C., Stiglitz J.E., 2000. Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? American Economic Review 90, 147-165.

Hollwitz, J., Wilson, C.E. 1993. Structured Interviewing in Volunteer Selection. Journal of Applied Communication Research 21, 41-52.

Jackson P., Perraudin W., Saporta V., 2002. Regulatory and economic solvency standards for internationally active banks. Journal of Banking & Finance 26, 953-976.

Jacobson T., Lindé J., Roszbach K., 2006. Internal rating systems, implied credit risk and the consistency of banks' risk classification policies. Journal of Banking & Finance 30, 1899-1926.

Jokipii T., Milne A., 2008. The cyclical behaviour of European bank capital buffers. Journal of Banking & Finance 32, 1440-1451.

Jeitschko, Thomas, and Shin Dong Jeung. 2005. Incentives for risk-taking in banking: A unified approach. Journal of Banking & Finance 29, 759-777.

Jones D., 2000. Emerging problems with the Basel capital accord: regulatory capital arbitrage and related issues. Journal of Banking & Finance 24, 35-58.

John K., Saunders A., Senbet L., 2000. A theory of bank regulation and management compensation. Review of financial studies 13, 95-125.

Kane E.J., 1995. Three paradigms for the role of capitalization requirements in insured financial institutions. Journal of Banking & Finance 19, 431-459.

Kahane Yehuda, 1977. Capital adequacy and the regulation of financial intermediaries. Journal of Banking and Finance 1, 207-218.

Kashyap A.K., Stein J.C., 2004. Cyclical implications of the Basel II capital standards. Federal Reserve Bank of Chicago Economic perspectives, 18-31.

Keeley, M.C., Furlong F.T., 1990. A re-examination of mean-variance analysis of bank capital regulation. Journal of Banking & Finance 14, 69-84.

Keeton W.R., 1988. Substitutes and complements in bank risk taking and the effectiveness of regulation. Federal Reserve Bank of Kansas City, Working Paper.

Keys B., Tanmoy M., Amit S., Vikrant V., 2008. Did securitisation lead to lax screening? Evidence from subprime loans. University of Chicago, Working Paper.

Kim D., Santomero A., 1988. Risk in banking and capital regulation. Journal of Finance 43, 1219-1233.

Koehn M., Santomero M., 1980. Regulation of bank capital and portfolio risk. Journal of Finance 35, 1235-1244.

Kretzschmar G., McNeil A.J., Kirchner A., 2010. Integrated models of capital adequacy – Why banks are undercapitalized. Journal of Banking & Finance 34, 2838-2850.

Lane W.R, Looney S.W., Wansley J.W., 1986. An application of the Cox proportional hazards model to bank failure. Journal of Banking & Finance 10, 511-531.

Liebig, T., Porath D., Weder B., Wedow M., 2007. Basel II and bank lending to emerging markets: Evidence from the German banking sector. Journal of Banking & Finance 31, 401-418.

Lopez A., 2004. The empirical relationship between average asset correlation, firm probability of default, and asset size. Journal of Financial Intermediation 13, 265-283.

Majnoni G., Shankar R., Varhegyi, E., 2003. The dynamics of foreign bank ownership: evidence from Hungary. World Bank Policy Research Working Paper 30.

Marini F., 2003. Bank insolvency, deposit insurance and capital adequacy. Journal of Financial Services Research 24, 67-78.

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

Mingo, J., 1975. Regulatory influence on bank capital investment. Journal of Finance 30, 1111-1121.

Morrison A., White L., 2005. Crises and capital requirements in banking. American Economic Review 95, 1548-1572.

Peltzman, S., 1970. Capital investment in commercial banking and its relationship to portfolio regulation. Journal of Political Economy 78, 1-26.

Reisen H., 2001. Will Basel II contribute to convergence in international capital flows? Paper prepared for Österreichische Nationalbank, 29th Economics Conference, OECD Development Centre, Paris.

Repullo R., 2004. Capital requirements, market power and risk-taking in banking. Journal of Financial Intermediation 13, 156-182.

Repullo R., Suarez J., 2010. The procyclical effects of bank capital regulation. European Banking Center Discussion Paper No. 2010-05S.

Rikkers F., Thibeault A., 2009. Rating SMEs. The financial executive quarterly 45, 13-18.

Rochet J.C., 1992. Capital requirements and the behavior of commercial banks. European Econonmic Review 36, 1137-1170.

Rochet J-C, 2004. Rebalancing the three pillars of Basel II. Economic Policy Review, 7-21.

Rowe, D. (2003). No cure through the cycle. http://www.risk.net/data/basel/freepdfs/basel_risk_0303_1.pdf

Saunders A., 2002. Credit Risk Measurement: value at risk and other new paradigms (2nd ed.), John Wiley and Sons, New York.

Sharpe W., 1978. Bank capital adequacy, deposit insurance, and security values. Journal of Financial and Quantitative Analysis, 701-718.

Schuermann T., Stiroh K.J., 2006. Visible and hidden risk factors for banks. Federal Reserve Bank of New York Staff Reports 252.

Thomson J.B., 1991. Predicting bank failures in the 1980s. Federal Reserve Bank of Cleveland Economic Review 27, 9-20.

Treacy, W. and Carey M. (2001). Credit risk rating systems at large US banks. Journal of Banking & Finance 24, 167-201.

Van Gestel T., Baesens B., 2009. Credit risk management: basic concepts: financial risk components, rating analysis, models, economic and regulatory capital, Oxford University Press, ISBN 978-0-19-954511-7.

Van Hoose D., 2007. Theories of bank behaviour under capital regulation. Journal of Banking & Finance 31, 3680-3697.

Vasicek O. (2002) Loan portfolio value. RISK, December 2002, 160-162.

Weelock D.C., Wilson W., 2000. Why do banks disappear? The determinants of U.S. Bank failures and acquisitions. Review of Economics and Statistics 82, 127-138.

Zingales L., 2008. Causes and effects of the Lehman Brothers bankruptcy. Testimony before the committee on oversight and government reform.
http://faculty.chicagobooth.edu/luigi.zingales/research/papers/zingales_long.pdf

Appendix

Appendix 1.1: Some intuition behind the IRB approach

The philosophy of the IRB approach is based on the frequency of bank insolvencies supervisors are willing to accept[23]. By means of a stochastic credit portfolio model, capital is set to assure that there is only a very small pre-defined probability for the amount of unexpected loss to exceed the amount of capital. Under Basel II, capital is set to maintain a fixed confidence level of 99.9%, implying that the probability of a bank to suffer losses that exceed capital is on average once in a thousand years. For the model used in Basel II to be widely applicable, it has to be a portfolio invariant model, i.e. the capital required for an exposure only depends on the risk of that exposure and not on the portfolio it is added to. As a result of this model restriction, the risk weight function under Basel II is based on an Asymptotic Single Risk Factor model (ASRF), where all systemic risk that affects borrowers is captured in one single risk measure (Gordy, 2003). The underlying assumption is that the bank's credit portfolio consists of a large number of small exposures. If this holds, the idiosyncratic risk associated with an individual loan is cancelled out and only the systemic risk remains. In the ASRF approach, there is only one systemic risk factor, implying that all loans in the portfolio are subject to the same set of market conditions. As a result, for a large portfolio of loans, the total capital requirement equals the weighted sum of the marginal capitals for individual loans. The model was further specified taking into account Merton's (1973) and Vasicek's (2002) ground work and resulted in the following risk-weight function:

$$K = \left[LGD * N\left[(1-R)^{-0.5} * G(PD) + \left(R/(1-R)\right)^{0.5} * G(0.999)\right] - PD * LGD\right] * \left(1 - 1.5 * b(PD)\right)^{-1} * \\ \left(1 + (M - 2.5) * b(PD)\right)$$

This formula calculates the conditional expected loss based on conditional PDs and downturn LGDs. The average PDs that are provided by banks and reflect normal business conditions are being transformed in conditional PDs reflecting default rates based on a conservative value of the systemic risk factor, through a supervisory mapping function. As there is no such function for LGDs banks are expected to provide LGDs reflecting economic-downturn conditions. The conditional expected loss includes both expected and unexpected loss, however as it was decided that capital should only cover unexpected loss (the UL concept), a correction for EL is required. Further, there is also a maturity adjustment taking into account that long-term credits are riskier than short-term credits and that these maturity effects are stronger for obligors with a low default probability. The degree of the obligor's exposure to the systemic risk component is reflected in the asset correlation (R). Under the IRB

[23] As mentioned before, in order to prevent moral hazard considerations for banks to take too much risk, it is not advisable to completely eliminate the credit risk.

approach, the asset correlations should be determined using a formula of the Basel Committee. These formulas are based on the observation that asset correlation increases with size and decreases with increasing PD (Lopez, 2004). It should be noted that the latter has been contested by several studies (e.g. Dietsch et al., 2004). As retail and SME credit are found to be less prone to systemic risk, these loans will receive another treatment than corporate loans and will require less regulatory capital for a given default probability. Besides the fact that the above function does not explicitly take into account portfolio and diversification effects, it also ignores the potential correlation between PD and LGD and by doing so it potentially underestimates the capital requirement.

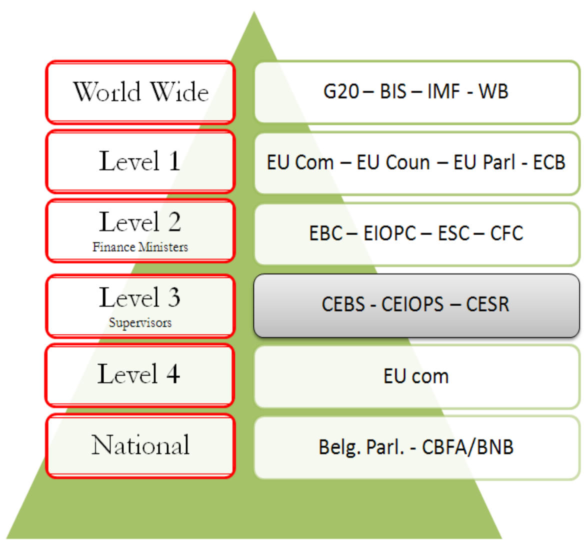
Appendix 1.2: Participants in this research

Academics and Opinion Leaders

The views of academicians and opinion leaders are crucial knowing that this topic is often described as being in between finance practice and philosophy. They consist of a diverse group of professors in economics and finance at Belgian universities, completed with one broker. Our sample can be considered as representative for the population. The interviews were semi-structured in order to allow certain flexibility and leave a room for creativity and further discussion. As a preparation for the interviews, we first consulted the viewpoint of the following parties: the Basel committee, the Group of Twenty (G20), Center for European Policy Studies (CEPS), the European Commission (CRD IV), de Larosière, The Committee of European Banking Supervision(CEBS), and the Euro Banking Association (EBA)), the European Parliament, the Federal Reserve (Fed) / Obama, the European organization for Cooperative Banks (EACB), the Organization for Economic Cooperation and Development (OECD) and the European Central Bank (ECB) / Trichet, added with some academicians and opinion leaders.

Regulators and Supervisors

Regulators and supervisors represent the second participants of this research. The regulatory and supervisory structure of the financial market is complex and should be addressed at different levels, which are depicted below[24]:



BIS: Bank of International Settlement
CEBS: Committee for European Banking Supervisors
CEIOPS: Committee of European Insurance and Occupational Pensions Supervisors
CESR: Committee of European Securities Regulators.
CFC: Committee on Financial Conglomerates
EBC: European Banking Committee
ECB: European Central Bank
EIOPC: European Insurance and Occupational Pensions Committee
ESC: European Securities Committee
EU Com: European Commission
EU Coun.: European Council
EU Parl.: European Parliament
IMF: International Monetary Fund
WB: World Bank

In order to be able to draw the view of regulators and supervisors, we performed an interview at every level of this pyramid, except for the "World Wide" level. The interviewee always had a close link with

[24] This scheme was developed during a joint collaboration between Vlerick Leuven Gent Management School and TriFinance.

the institution. These interviews were semi-structured and were framed around the same topics addressed in the other parts of this research. The list of participant for regulators and supervisors is presented below.

UK Cabinet for Business, Innovation, and Skills,
European Commission,
Banking Finance and Insurance Commission / CBFA (Belgium),
Banque Nationale de Belgique (Belgium),
Financial Services Authorities (United Kingdom).
Swiss Financial Market Supervisory Authority – FINMA

Appendix 1.3: Detailed description of banks in our sample

In the table below you can find an overview of the banks that collaborated in our survey.
Most of our banks are retail banks and also universal banks, defined as banks that have multiple business activities, present a large piece. Beside the bank type, we further split up the banks according to their ratings. More specifically, we looked at ratings from S&P, Moody's and Fitch and made a consensus for each bank. Usually ratings were similar across rating agencies or only available by one CRA. If the bank scores on average an A- or higher, the institution belongs to group 1. If the bank has a rating below A-, we regard it as a bank of group 2. Finally the third group consists of banks that are unrated, which are mainly domestic and smaller banks.
Regarding size it is difficult to compare banks across countries. Nevertheless we did an attempt to classify banks according to their relative size –measured by assets- using other financial institutions in the same country as a benchmark. For example in Germany, the four high street banks would be regarded as big, while the others are considered as small and medium.

The table below gives an overview of the banks that collaborated in our survey. It reflects the situation of the banks at the moment the interview took place.

	Country	Name	Size	S&P	Moody's	Fitch
1	Belgium	Argenta Spaarbank	S & M	BBB+	Unrated	Unrated
2	Belgium	Bank Delen	S & M	Unrated	Unrated	Unrated
3	Belgium	Caisse d'Epargne de Tournai	S&M	unrated	unrated	unrated
4	Belgium	Delta Lloyd	S&M	AA-	unrated	AA-
5	Belgium	Dexia	Big	A	A1	A+
6	Belgium	Fortis	Big	A+	A1	A+
7	Belgium	Landbouwkrediet	S&M	Unrated	Unrated	Unrated
8	Belgium	KBC	Big	AA-	Aa2	AA-

9	**Bulgaria**	**Raiffeisen Bank**	**Big**	**Unrated**	**Baa3**	**Unrated**
10	**Czech Rep.**	**Investicni spolecnost Ceske sporitelny**	**Big**	**Unrated**	**Unrated**	**Unrated**
11	**Denmark**	**Jyskebank**	**Big**	**A+**	**Aa2**	**A+**
12	**Denmark**	**Nykredit**	**Big**	**A+**	**A1**	**unrated**
13	**Denmark**	**Saxo Bank**	**Big**	**Unrated**	**Unrated**	**Unrated**
14	**Denmark**	**Sydbank**	**Big**	**unrated**	**A1**	**unrated**
15	**Finland**	**Tapiola**	**S&M**	**unrated**	**unrated**	**unrated**
16	**Finland**	**Aktia Bank**	**S&M**	**unrated**	**A1**	**unrated**
17	**Finland**	**Municipality Finance Plc.**	**S&M**	**AAA**	**Aaa**	**unrated**
18	**Finland**	**Alandsbanke n**	**S&M**	**unrated**	**unrated**	**unrated**
19	**Finland**	**Sampo Pankki**	**Big**	**A**	**A1**	**unrated**
20	**Germany**	**AXA Bank Germany**	**S&M**	**A+**	**unrated**	**A**
21	**Germany**	**Deutsche Postbank**	**Big**	**A-**	**A1**	**A+**
22	**Germany**	**Deutsche Bank**	**Big**	**A+**	**Aa3**	**AA-**
23	**Hungary**	**AXA Bank Hungary**	**S&M**	**A+**	**unrated**	**A**
24	**Hungary**	**K&H Bank**	**Big**	**A-**	**unrated**	**A-**
25	**Kazachstan**	**Halyk Bank**	**Big**	**B+**	**Ba2**	**B+**
26	**Luxembourg**	**Advanzia Bank**	**S&M**	**unrated**	**unrated**	**unrated**
27	**Luxembourg**	**Bank of China - Luxembourg**	**S&M**	**unrated**	**A1**	**A**

28	**Norway**	**Storebrand**	**S&M**	**BBB+**	**A3**	**BB+**
29	**Spain**	**Santander**	**Big**	**A**	**Aa2**	**AA**
30	**Sweden**	**Svenska Handelsbanken**	**Big**	**AA-**	**Aa2**	**AA-**
31	**Sweden**	**JAK Medlemsbank**	**S&M**	**unrated**	**unrated**	**unrated**
32	**Sweden**	**SEB**	**Big**	**A+**	**Aa2**	**A+**
33	**Switzerland**	**InCore Bank AG**	**S&M**	**unrated**	**unrated**	**unrated**
34	**Switzerland**	**Sarasin**	**S&M**	**unrated**	**unrated**	**unrated**
35	**The Netherlands**	**AEGON**	**S&M**	**A+**	**unrated**	**A**
36	**The Netherlands**	**BinckBank**	**S&M**	**unrated**	**unrated**	**unrated**
37	**The Netherlands**	**ING**	**Big**	**AA**	**Aa1**	**AA**
38	**The Netherlands**	**Mizuho Corporate Bank Nederland NV**	**S&M**	**unrated**	**Aa3**	**A**
39	**The Netherlands**	**NIBC**	**S&M**	**BBB**	**Baa2**	**BBB**
40	**The Netherlands**	**Rabobank**	**Big**	**AAA**	**Aaa**	**AA+**
41	**The Netherlands**	**Lanschot Bankiers**	**S&M**	**unrated**	**unrated**	**unrated**
42	**UK**	**Barclays**	**Big**	**AA**	**Aa1**	**AA**
43	**UK**	**European Finance House**	**S&M**	**unrated**	**unrated**	**unrated**
44	**UK**	**HBOS**	**Big**	**AA-**	**Aa1**	**AA**
45	**UK**	**HSBC**	**Big**	**AA-**	**Aaa**	**AA-**

Tables

COUNTRY	CHARACTERISTIC	SUBDIVISION	EXAMPLE
Austria			
	Type	Joint stock Banks	Oberbank
		State Mortgage Banks	Niederösterreichische Landeshypothekenbank
		Savings Banks	Sparkasse Group
		Credit Cooperatives	Raiffeissen Group AG
	Sectors	Single-stage	BAWAG
		Double-stage	Volksbank cooperatives
		Triple-stage	Raiffeissen cooperatives
Belgium			
	Size	Large	KBC Bank
		Medium	AXA Belgium
		Small	Keytrade Bank
Czech Republic			
	Size	Big	Komercni Banka
		Small	Ceská exportní banky
Denmark			
	Size	Big	Danske Bank
		Medium	Nykredit Bank
		Small	FIH
	Type	Universal Banks	Nordea Denmark
		Investment Banks	Saxo Bank
		Other Banks	CantoBank
Estonia			
	Size	Big	Eestu Ühisbank
		Small	Praetoni Pank
Finland			
	Type	Commercial Banks	Nordea
		Saving Banks	Nooa Sparbank
		Cooperative Banks: OP-Pohjola	Porvoon Osuuspankki
		Cooperative Banks: Local	Lokalandelsbanken
	Size	Major	Sampo Pankki
		Minor	Ålandsbanken
France			
	Type	Public Bank	La Banque postale
		Cooperative Banks	Crédit Mutuel
		Commercial & Universal Banks	BNP Paribas
Germany			
	Type	Cooperative Bank	Volksbank
		Savings Bank	Hamburger Sparkasse
		Commercial Bank	Deutsche Bank
	Size	National	Raiffeissen Group
		Regional	Bank Schilling & Co.
Greece			
	Type	Cooperative bank	Cooperative Bank of Epirus
		Big Bank	Agricultural Bank of Greece
Italy			
	Type		
		Universal bank	Intesa SanPaolo
		Cooperative bank	Banco Populare

	Size		
		Big	Unicredit
		Small	Acquaviva Picena
Latvia			
	Type	Saving Bank	Latvian Saving Bank
		Private Bank	Aizkraukles Bank
	Size	Big	Hansabanka
		Small	Norvik Banka
Lithuania			
	Size	Big	LB Lietuva
		Small	Jureiviu Credit Union
Luxembourg			
	Type	Saving Bank	Banque et Caisse d'Epargne de l'Etat
		Commercial Bank	BGL
		Cooperative Bank	Compagnie de Banque Privée
	Size	Big	BNP Paribas Luxembourg
		Small	Advanzia Bank S.A.
Norway			
	Size	Big	DnB NOR
		Medium	Sparebank 1 Gruppen
		Small	Terragroup
	Type	Commercial Banks	Nordea
		Saving Banks	Sparebank 1 Gruppen
Russia			
	Size	Big	Sberbank
		Small	Avtobank
Slowakia			
	Size	Big	Nova Ljubljanska Banka
		Small	Wustenrot Stavebna sporitelna
Spain			
	Type	Clearing Banks	BBVA
		Saving Banks (Cajas)	Caja Madrid
	Size	National	La Caixa
		Regional	Caja Sur
Sweden			
	Type	Commercial Banks	Swedbank
		Saving Banks	Dalslands Sparbank
		Cooperative Banks	Ekobanken
	Size	Large – universal	SEB
		Small – reformed	Falkenbergs Sparbank
		Small – new	Avanza Bank
Switzerland			
	Type	Universal Bank	Crédit Suisse
		Raiffeisen Bank	Raiffeisen Schweiz
		Cantonal Bank	Zürcher Kantonalbank
		Savings Banks	Caisse d'Epargne de Nyon
		Private Bank / AM	Julius Bär
The Netherlands			
	Size		
		Big	ABN-Amro
		Small	BinckBank
United Kingdom			
	Primary Activity	Universal	Barclays Plc.
		Retail Bank	NatWest
		Corporate Banks	Mizuho Corporate Bank

			London Branch
		Investment Banks	Morgan Stanley
		Other Banks	Gatehouse bank

Table 1.1: The European Banking Landscape

Figures

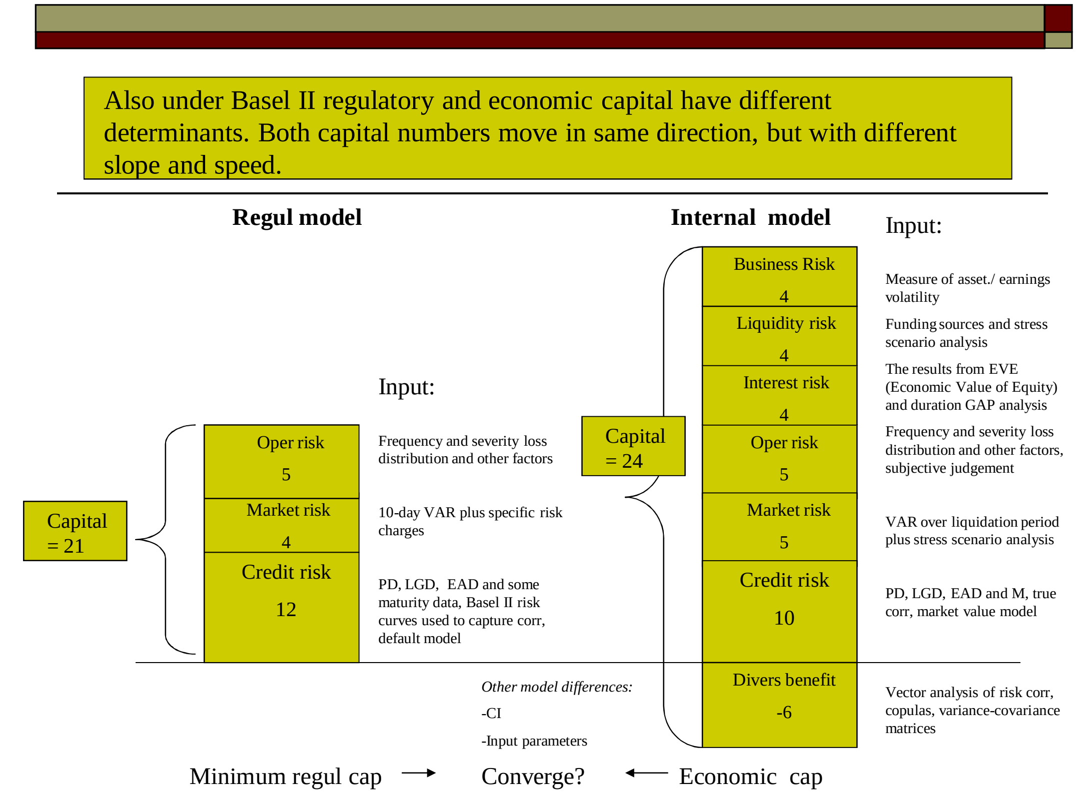


Figure 1.1: Difference between economic and regulatory capital, an example[25]

[25] Based on Burns R. (2005).

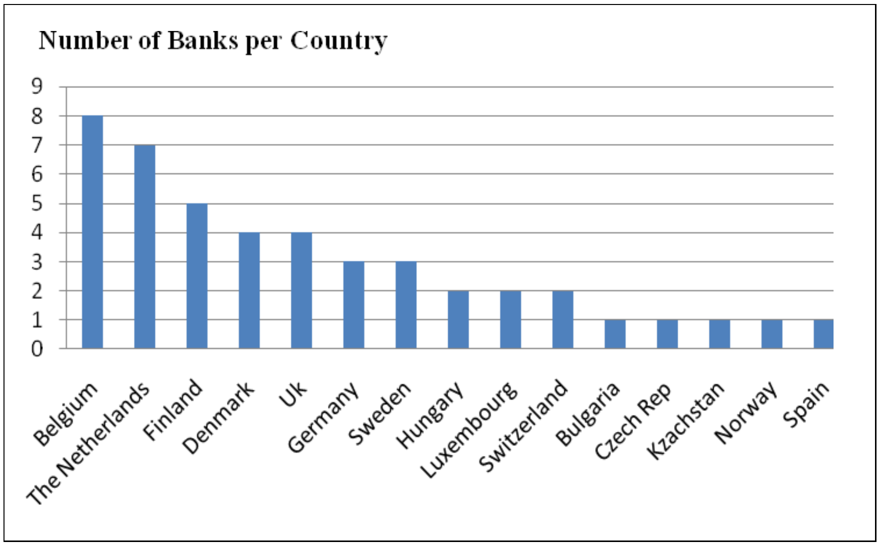


Figure 1.2: Banks across countries

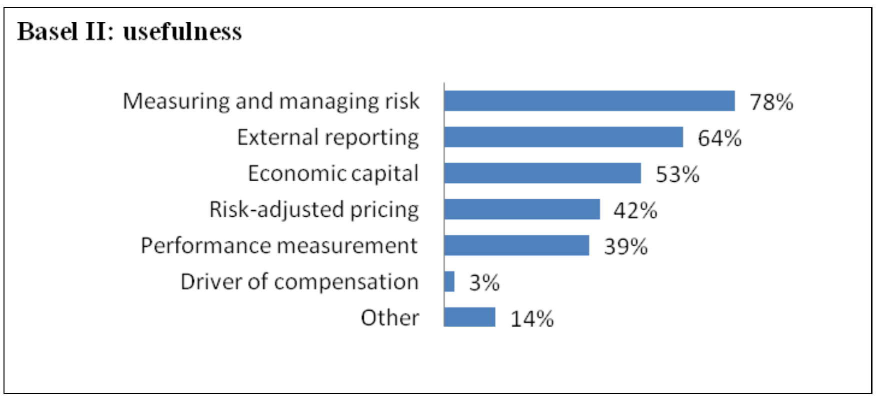


Figure 1.3: The perceived usefulness of Basel II

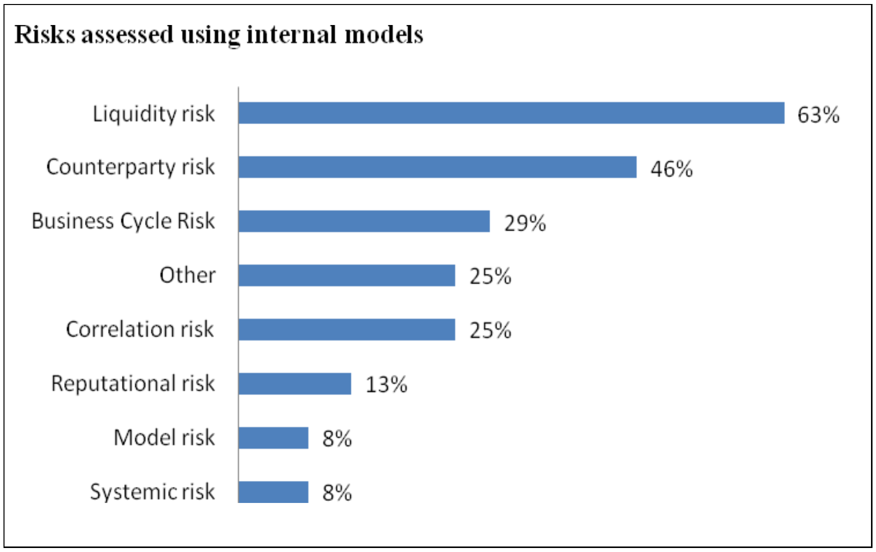


Figure 1.4: Risks assessed using internal models

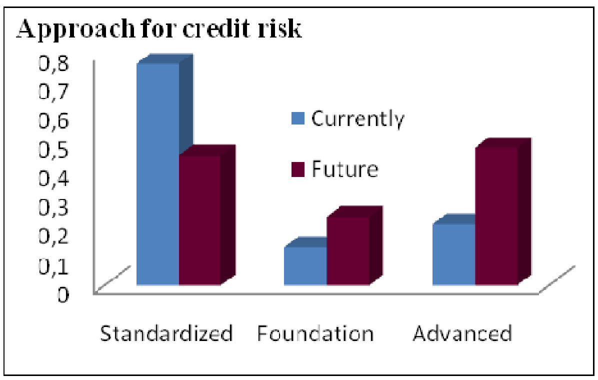


Figure 1.5: Basel II approach for credit risk now and in future

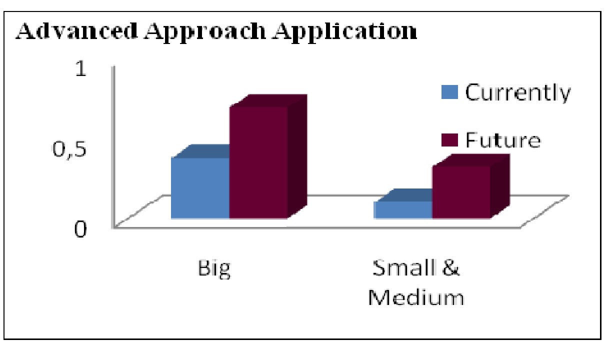


Figure 1.6: Adoption of Advanced IRB approach by big and small banks now and in future

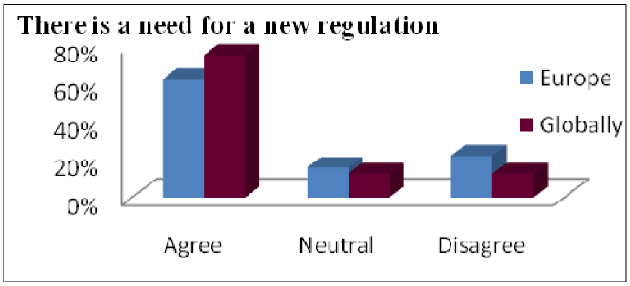


Figure 1.7: Perceived need for a new regulation

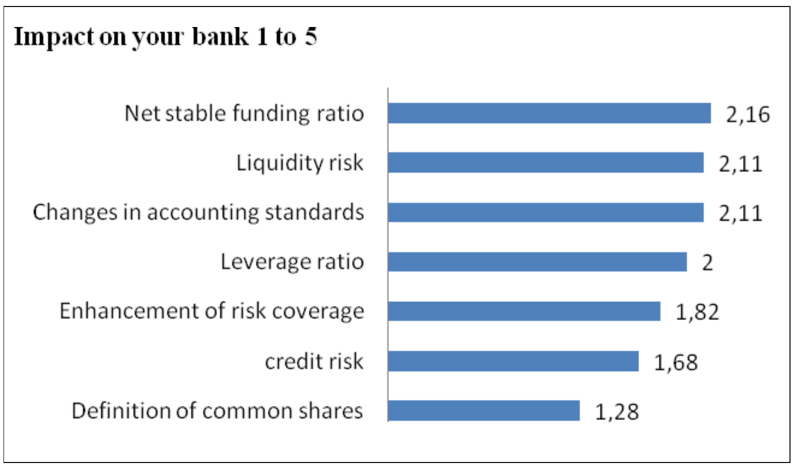


Figure 1.8: The expected impact of the regulatory changes on your bank

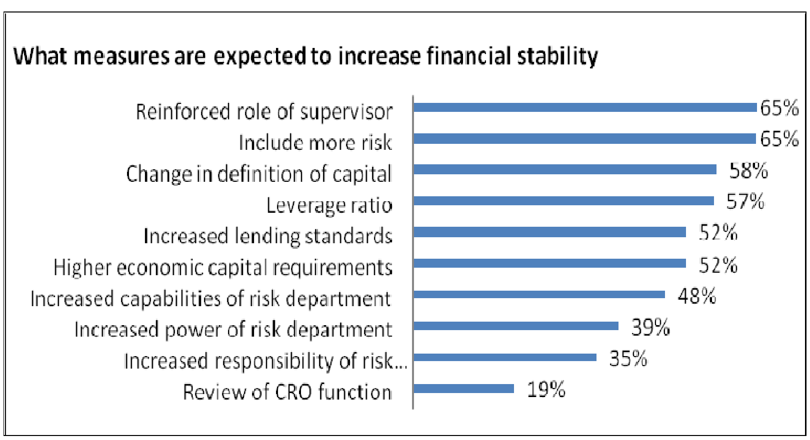


Figure 1.9: The expected impact of the regulatory changes on financial stability

"In these shaky times, it is in Europe's interest not to fall out publicly over a key issue of financial regulation; that key issue being Solvency II." Bernard Spitz, Chairman of the French Federation of Insurance Companies **-** Wall Street Journal Europe – March 19, 2009.

Chapter 2: The development of a simple and intuitive rating system under Solvency II*

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Abstract

Regulatory authorities pay considerable attention to setting minimum capital levels for different kinds of financial institutions. Solvency II, the European Commission's planned reform of the regulation of insurance companies is well underway. One of its consequences will be a shift in focus to internally-based models in determining the regulatory capital needed to cover unexpected losses. This evolution emphasises the importance of credit risk assessment through internal ratings. In light of this new prudential regulation, this paper suggests a Basel II compliant approach to predicting credit ratings for non-rated corporations and evaluates its performance compared to external ratings. The paper provides an interesting modelling of non-financial European companies rated by S&P. In developing the model, broad applicability is set as an important boundary condition. Even though the model developed is fairly simple and maintains a high level of granularity, it gives high rates of accuracy and is very interpretable.

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2.1 Introduction

Over the past decade, the economic environment has been characterised by high-profile business scandals and failures, in which different company stakeholders were involved. As a result the concern surrounding risk management and focus on it have increased dramatically. Moreover, the current credit crisis and recession call for enhanced risk management practices with more stringent laws and regulations. This is especially true for financial institutions, whose insolvency might result in substantial losses with huge spill-over effects to different parts of the economy. In order to promote financial stability, regulatory authorities pay considerable attention to setting minimum capital levels for the different kinds of financial institutions. Traditional regulation developed standard control mechanisms based on external ratings provided by agencies such as Moody's and Standard & Poor's. However the new economic and regulatory environment call for more sophisticated, internally developed risk management systems, which employ internal risk estimates to categorise exposures. The default history of financial institutions shows that credit risk is the most important threat to insolvency. Even though other risks are recognised, financial regulation mainly highlights the utility of credit risk assessments, particularly for estimating the probability of default.

In line with the Basel II requirements for banks, the European Commission has established the Solvency II Directive for insurance companies. Currently, the insurance industry is moving quickly to become compliant with this framework by the third quarter of 2012. The new directive, in parallel with Basel II, is based on three reinforcing pillars: capital requirements, supervisory review and reporting and disclosure. Under Solvency II, two capital levels will be established: the minimum capital requirement, a threshold at which companies will no longer be permitted to trade, and a solvency capital requirement, a going concern risk measure, targeting a 99.5 per cent value-at-risk (VAR), below which companies may need to discuss remedies with their regulator. The solvency capital requirement includes four major risk categories: credit risk, market risk, operational risk and underwriting risk and can be calculated by a standardised approach, an internal model or a combination of both (e.g. Eling et al., 2007)[26]. The initial focus of Solvency II has been on the standardised approach, a one-size-fits-all formula that could be applied by all insurers irrespective of portfolio, size, business niche etc. However, insurance companies will be stimulated to develop adequate internal models that better fit their risk profile. An important safeguard in the internal rating based approach is that such ratings can only be used upon approval by supervisory authorities. The exact requirements for internal models are not final, but are likely to be based on three tests. Firstly, the use test for which the insurance company will have to show that the outcome of the models is used by management in decision making. By aligning managerial and supervisory objectives, potential agency conflicts between both parties are reduced. Secondly, the calibration test, where the model

[26] The scope of this paper will be limited to the credit risk confronting insurance companies (infra).

must be calibrated using risk measures and calibration levels defined under Solvency II. And finally, the statistical test where it must be shown that the model is based on relevant and quality-assured data. Hence the need for more sophisticated and adaptive risk tools that enable an insurance company to evaluate and improve risk management has never been more compelling. When the statistical power of an internal rating system is poor, it will deteriorate the economic performance of the insurance company due to adverse selection. Obviously, improving the statistical power of a rating system will decrease potential adverse selection, and combined with other standards can result in a reduction of regulatory capital requirements. Besides regulatory compliance and the reduction of adverse selection, there are several other advantages for an insurance company in having a reliable internal credit rating system. For instance, a reliable rating model can facilitate an accurate, fair and objective pricing policy; it will offer an objective basis to sell to the re-insurers and due to the more objective pricing it might even reduce the need for reinsurance (Tiller and Tiller, 1995). Jankowitsch et al. (2007) show that when financial institutions improve their internal rating system from low accuracy to medium accuracy, the annual return of their portfolio can be increased by 30-40 basis points.

In order to be Solvency II compliant, the internally developed models should be transparent, robust and efficient, creating one of the biggest challenges insurance companies are currently faced with (Carey and Hrycay, 2001; Chorafas, 2004; Grunert et al., 2005), especially because these companies often lack sufficient internal data and modelling experience. A big challenge in setting up an internal model is the inference of the probability of default (PD). In order to estimate the PD that is linked to an internal rating grade, appropriate techniques must be used. One method of arriving at a transparent result is to associate an internal rating with an external rating and then attribute the external default rate to that internal grade. This mapping must be based on an extensive comparison between internal and external rating criteria. When doing so, it is crucial for financial institutions to understand the external rating process (Brunner et al., 2000; Grunnert et al., 2005) and when possible, to align the internal and external rating process and architecture (Carey et al., 2001).

Both practitioners and academics have undertaken a substantial body of research on Basel II and more in general on risk management within financial institutions (e.g. Van Gestel et al., 2009). Notwithstanding the fact that insurance companies are very important players in financial markets, who are involved in many credit risk exposures and as a consequence are also prone to high levels of uncertainty and solvency issues, literature on the topic is scarce (Florez-Lopez, 2007). Furthermore, the existing rating literature is clearly focused on banks rather than insurance companies (e.g. Gaver and Pottier, 2005; Van Gestel et al., 2005; West, 1985). Banks and insurance companies differ structurally, limiting the extent of convergence and comparison for the two financial intermediaries (Florez-Lopez, 2007). Beltratti and Giuseppe (2008) have investigated the drivers of this divergence and have found that the most important factors are the liability structure, scale of operations and demographics, which are all linked to the underlying customer portfolio. Besides the factors linked to the underlying customer portfolio, other factors such as the fact that insurance companies often have less diversified shareholders[27] might also create biases (Berger et al., 1992).

In the light of Solvency II, whose key objective for capital requirements is to better reflect the true risk of an insurance company, this paper seeks to develop a simple and intuitive credit rating model with a high degree of accuracy and reliability for the European corporate exposures of an insurance company. A substantial body of research has already been undertaken in this field. However, this paper contributes to the existing literature in several ways. Our first addition to the literature is the fact that we develop the model in an insurance setting taking into account the regulatory Solvency II boundaries. Secondly, in developing our model, we address potential biases and instabilities the mapping exercise might entail. Furthermore, we focus on European corporations whereas existing literature is mainly focused on US or UK corporate exposures. The credit risk rating literature concerning European corporate exposures is rather limited. However, existing differences between these markets might undermine the extrapolation potential to a European environment[28]. Finally, compared to other studies, we are able to obtain very high accuracy with a simple and economic intuitive model.

The paper continues as follows. The next section contains a discussion of related literature covering the most appropriate methodologies for modelling insolvency risk and credit risk ratings. Next, we set out the data, empirical strategy and model estimations. Finally, we present the results, including diagnostic tests of model performance.

[27] The shareholders of insurance companies are often closely held stock companies or mutual funds who tend to hold higher than optimal proportions of their wealth in the insurer (Mayers and Smith, 1990).

2.2 Literature review

The literature review gives an overview of the existing rating literature with a focus on credit risk modelling methodologies and risk rating determinants.

2.2.1 Credit ratings

Solvency II is providing considerable impetus to European insurance companies to develop adequate internal rating models. The estimation of the probability of default is a crucial component for the development of such a model. Setting this PD can be based on internal default experience or on an external mapping procedure. The first refers to the use of historical data about the institution's own clients and requires an extensive dataset which most institutions currently lack. The latter refers to the mapping of the internal grades to an external risk scale. This mapping procedure is based on a comparison of the determinants of internal ratings with the criteria used by external rating agencies. A big advantage of this methodology is its simplicity and also the fact that the financial institution can benefit from the experience and knowledge of the external rating agency. Furthermore, agency grades are familiar to most market participants and empirical research has revealed quite a number of similarities between internal rating models and external ratings (e.g. Crouhy et al., 2001; Grunert et al., 2005). However, even though there might be some similarities, internal ratings that are being developed will always differ from each other and from external ratings (English et al., 1998; Krahnen and Weber, 2001; Treacy and Carey, 1998). Difference in rating philosophy and incompatibilities between internal and external rating criteria might create biases and instability (cf. infra) during this mapping exercise.[29] In a paper investigating the parameterisation of credit risk models, Carey et al. (2001) conclude that ,as internal rating and the agency rating system have different architectures, it is highly unlikely that human judgment can result in a stable and reliable mapping quantification. Furthermore, Carey et al. (2001) show that stable quantification can only be obtained when very long panels of data are being used. In order to circumvent potential biases and instability and in order to fully exploit the expertise of rating agencies, we will develop a credit rating model that mimics external ratings and as such combines credit scoring and mapping in one exercise.

The use of external ratings in building an internal rating model is especially relevant when little data is available. Under Basel II, these alternative external data sources are recommended for use in risk quantification and validation. Taking into account the fact that most insurance companies have limited internal data and modelling experience, the mapping procedure looks like the best short-term solution for building an internal model and for estimating PDs. Moreover, also under Solvency II, external

[29] Another important drawback is the fact that there are only a few qualified external rating companies (Florez-Lopez, 2007).

ratings will continue to play an important role, albeit for assisting supervision. As such it is highly relevant both for supervisors and insurance companies to understand rating agencies' methodologies and determinants.

External ratings are based on publically available information such as the balance sheet and P&L, but also on non-public information such as interviews with the company's management. Standard & Poor's, for instance, publishes 10 financial ratios that are key in their analysis, but at the same time states that "subjectivity is at the heart of every rating" (S&P, 2002). So these ratings are not fully transparent and by consequence not that easy for financial institutions to use. A considerable amount of research has already been done to understand the rating determinants of industrial corporations and bonds (e.g. Altman, 1989; Amato et al., 2004; Blume et al., 1998; Crouhy et al., 2001; Ohlson, 1980). Several models have already been used to explore rating determinants using different statistical techniques and including different types of explanatory variables. The credit ratings of the insurance company itself have also been investigated. A number of empirical studies have compared models that predict an insurer's insolvency based on financial data. For example Trieshmann and Pinches (1973) used multiple discriminant analysis, Berger et al. (1992) used linear regression, Altman et al. (1994) and Brockett et al. (2006) compared the use of neural networks to the more traditional statistical methods such as Multiple Discriminant Models[30], logit and probit etc.

The literature on external ratings can be divided into different strands. An important category relates to the determinants of ratings. One series of papers in this category investigates whether ratings measure what they are supposed to measure (Ang and Patel, 1975; Hickman, 1958; Kao et al., 1990) and finds that ratings do have an informational content. Secondly, there are papers investigating whether ratings convey information that is not reflected in bond prices, in which mixed results have been obtained up till now (Hand et al., 1992; Katz, 1974). Thirdly, there are various papers investigating the information that is reflected in ratings. These papers can be divided based on the methodology that is used and on the independent variables that are investigated.

Over the past decades and under continuously changing forces, academics have tried to find the ultimate credit risk measures and models. As a result different scoring procedures have been developed. First there were univariate models that compared a number of financial ratios for a paired sample of failing and non-failing companies (e.g. Beaver, 1966). In response to this, simple intuitive point systems called risk index models were developed (e.g. Tamari, 1966). At about the same time, multivariate models evolved. These are models that combine and weigh financial ratios and result in a score or a default probability. These multivariate models can be split into different models such as

[30] Multiple Discriminant Models will be referred to as MDA models.

linear probability models, (ordered) logit models, (ordered) probit models, discriminant analysis models etc. (see Altman et al., 1998). Horrigan (1966) and West (1970) were the first to assign ordinal numbers to ratings and to regress them on accounting-related and other variables. For years afterwards, the dominant methodology was the multiple discriminant analysis (e.g. Altman et al., 1977; Pinches and Mingo, 1973, 1975) where companies are classified as failing or non-failing according to several financial characteristics. These characteristics are combined into one single multivariate discriminant score by means of a linear discriminant function or a quadratic discriminant function. In a next step this score is compared to a cut-off point. The most well-known example of a linear multiple discriminant model is Altman’s Z-model (1968). Later, he extended this approach to a quadratic multiple discriminant model called Altman’s Zeta-model (Altman et al., 1977). For a long time multivariate accounting based credit scoring models have proven to outperform a lot of the other models (e.g. Scott, 1981; Trieshman, 1973). However, the fact that these models are often based on book values and the knowledge that in reality default patterns are non-linear and often lack a theoretical basis, gave rise to new models such as logit, probit and ordered probit models (e.g. Kaplan and Urwitz, 1979). Unlike the MDA models they are not restricted by strict assumptions regarding the distribution of the independent variables. Another advantage is that these models allow for qualitative variables such as country risk or industry risk (Balcaen and Ooghe, 2004). Barniv et al. (1990, 1992) show that logit and probit models outperform MDA in most cases. Another type of models are those known as 'risk of ruin' models (e.g. Santomero and Vinso, 1977; Wilcox, 1973), which are quite similar to the option pricing models of Black and Scholes (1973) and Merton (1974). In these models, default estimates are derived from the expected movements of stock prices over a specific period of time. Besides the more classical statistical methods, academics have also explored alternative ways to address failure prediction like machine learning, survival analysis and neural networks (e.g. Beynon et al., 2005, Chaveesuk R. et al., 1999; Daubie et al., 2002, Fantazzini and Figini, 2009; Florez-Lopez, 2007; Frydman et al., 1985; Lane et al., 1986; Yang et al., 1999). In some circumstances these expert system methods can outperform MDA and logit analysis (Coats and Fant, 1993; Brockett et al., 2006). However, notwithstanding the fact that for instance neural networks are able to discriminate patterns that are not necessarily linearly separable, the often large number of parameters that are involved in a neural model may cause generalization problems and make these models true black-boxes.

Starting from the input data of credit risk models, existing literature can mainly be divided into two important strands: on the one hand default prediction models using historical accounting data (e.g. Altman, 1968; Ohlson, 1980) and on the other hand models relying on securities market information (e.g. the Merton Model, 1974). Even though recent research suggests that market data models outperform accounting data models (e.g. Shumway, 2001, Hillegeist et al., 2004), there is no consensus on this matter. Furthermore, throughout Europe, private firms make up the majority of firms. In Belgium for instance, anno 2008, about 450 00 companies were registered and only about

200 were quoted on a stock market, limiting data availability. However, the existing research is mainly based on US (e.g. Zavgren, 1985) and UK data (e.g. Peel et al., 1986, 1988) with a clear focus on large and quoted firms. Only few studies have focussed on smaller, unlisted firms (e.g. Hill and Wilson, 2007).

Looking at the variables that have been investigated, a first set of explanatory variables is more quantitative by nature and includes variables such as profitability, liquidity, interest coverage etc. (Altman and Narayanan, 1997; Altman et al., 2004; Amato et al., 2004; Blume et al., 1998; Estrella et al., 1999; Tabakis et al., 2002). Early studies (e.g. Horrigan, 1966; Pinches et al., 1975; Pogue et al., 1969) already found that financial data are a key input for corporate bond ratings. Later more qualitative variables were also added to the analysis: age, type of business, industry (e.g. Altman et al., 2008; Bunn and Redwood, 2003; Chava et al., 2004; Platt and Platt, 1991) along with the inclusion of macro-economic indicators (Hol, 2006; Wilson et al., 2009).

2.3 Research design and methodology

In this paper, we develop an internal credit rating model for corporate exposures in the portfolio of an insurance company. Taking into account the limited data and modelling experience of most insurance companies combined with the fact that external ratings have proven to be a reasonably good indicator of corporate credit quality (e.g. Carey et al., 2001; Kao and Wu, 1990; etc), we suggest exploiting the expertise of external rating agencies by mimicking their ratings. As was mentioned before, it is often argued that internal rating systems differ a lot from the systems used by external agencies and that as a result the mapping becomes unstable. By combining the credit scoring and mapping in one exercise, we address some of the potential biases and instability issues that might arise.

By means of an ordinal logistic regression we will estimate the determinants of the external ratings. In a next step these variables will serve as an input for the internal rating model. Afterwards we estimate how well they fit both in and out of sample. In developing our model, broad applicability is set as an important boundary condition. Over the past years, many models tried to increase prediction accuracy by incorporating information that is only available for a small set of often quoted counterparties. Taking into account the fact that credit risk properties of public and private firms differ (Altman et al., 2000) and the fact that European corporations are typically small and medium sized enterprises, it is important to develop a model that is widely applicable.

Our approach is depicted in Figure 2.1.

Insert Figure 2.1 here

2.3.1 Data collection

We have developed a model for the corporate portfolio of an insurance company. As we want to focus on European credit rating determinants, we have chosen a Belgian insurance company with mainly European corporates as its customers. Insurance companies are typically confronted with underwriting risk, market risk, operational risk and credit risk. However, as the focus of this paper is on credit risk, we have chosen an insurance company that throughout its activities is mainly exposed to credit risk.

In a first step we have collected the external ratings of the European corporations that are represented in the portfolio of the insurer. The insurance company has a large corporate customer base, but few customers get an external rating. We have decided to limit our sample to the customers of the insurance company that receive an external rating, as they are most representative for the full customer base. At first we collected both S&P and Moody's ratings. However, as we obtained fewer observations using Moody's ratings and as most academic research we refer to is also based on S&P ratings we continued with the S&P data. This eventually resulted in a dataset of 350 rated European corporate entities.

A rating maps the expected probability of default into a discrete number of rating classes (Krahnen et al., 2001). The rating classes of S&P, which are given on a scale from AAA to D, were transformed into a numerical scale from AAA = 1, AA+ = 2 etc. until CCC-D=17[31]. The observations with a rating ranging from CCC to D were rather limited and as such were combined in one single numerical code. Previous papers mostly combine the original S&P rating classes in new rating grades, reducing the granularity of ratings (e.g. Florez-Lopez, 2007 etc). As we feel a lot of information gets lost in this process, we have kept the same number of rating classes as S&P. So our dependent variable considers 17 rating grades, including + and – modifiers.

The independent variables are based on both academic research (e.g. Fernandes, 2005; Ooghe et al., 2005; Stickney et al., 2006 etc.) and industry experience.

For the financial and annual account data of the 350 identified corporates, we make use of the Amadeus dataset. If available, the financial information was collected for the most recent financial statement numbers and the two preceding years. For most companies we had the data of 2005, 2004 and 2003. External rating agencies follow a through-the-cycle rating philosophy implying that the ratings give an indication of the borrower's creditworthiness, based on a full business or economic cycle. The difference in architecture that is induced by the fact that we only use 3 years of data might

[31] A bond with an S&P rating of BBB or above is an investment grade bond, one with a BB or below is a non-investment grade bond or junk bond, a bond with a D rating is in default.

affect the model performance and procyclicality of the internal ratings. Procyclicality refers to the incorporation of a cycle effect into credit risk models, implying that there is a positive correlation between the rating and the overall state of the economy. Furthermore, it might be expected that our quantification exercise will be influenced by the historical period used in estimating our scoring model. The European economic environment in that period was characterized by a growth in GDP of 1.9%, 2.5% and 1.3% respectively (Eurostat, 2008). However, the fact that we have only used relatively recent data has the advantage that the credit risk regime is constant and is representative for the estimated ratings. Carey et al. (2001) show that regime shifts, which are circumvented by our sample and are omnipresent in larger samples, might cause significant problems in mapping and scoring procedures.

Using the financial information, we have calculated 24 ratios. Previous studies have employed a wide range of independent variables, but 4 indicators of financial health are persistently used. These 4 indicators are related to financial leverage, operational cash flow, the amount of liquid assets and size. The link between credit risk and the first three dimensions is straightforward. The higher the leverage, the lower the liquid asset base and the lower the operational cash flow, ceteris paribus, the more a company is prone to default risk. The rationale with respect to the final parameter, size, is that larger firms tend to be older and as such are expected to be more stable, which results in a lower risk profile. Furthermore, larger firms also have access to a broader range of financing alternatives compared to smaller firms. Blume et al. (1998) were the first to show that accounting ratios are more informative for larger companies, which makes it very relevant to control for the impact of size in our model.

In our model these four dimensions are extended with other variables linked to profitability, added value etc. Based on the findings of Cantor and Packer (1996) we also include country risk as a variable. The country risk was based on the Standard & Poor's rating of the country where a company is located. Finally, we also included an industry variable. The industry classification was based on the GICS code (Global Industry Classification Standard). The GICS methodology developed by S&P is widely accepted as an industry analysis framework for credit risk research (MSCI and Standard & Poor's, 2002). Ten different industries are identified with the GICS classification: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Healthcare, Financials, Information Technology, Telecommunication Services, and Utilities. In appendix 2.1 you can find an overview of the different independent variables that were included in our model.

In the next step we started pre-processing our data. Using a k-means and hierarchical cluster analysis, we investigated whether some grouping or elimination of certain industries could further enhance the results (see appendix 2.2). This analysis is inspired by a report of Moody's (2006) that reveals big differences between industry ratios and concludes that more intrinsically risky industries are required to achieve better credit ratios to obtain a given rating. The goal of our cluster analysis was to exclude those industries with the most dissimilar financial ratios for a given rating class and resulted in the exclusion of the Oil and Gas industry (see also Metz and Cantor, 2006). Financial institutions such as banks and financial service providers were also eliminated from the sample. Because of the nature of business, the credit risk implications of any set of accounting ratios is quite different for financial and non-financial firms. These companies have entirely different balance sheets and P&L's compared to corporations in other sectors. Including them in the regression analysis would therefore severely distort the results.

Companies were also eliminated when at least one third of the calculated variables were missing and/or if the consolidated figures were not found on Amadeus. Companies whose rating was influenced by the government, a parent company or any other legally related entity were also eliminated from the sample. This resulted in a sample of companies where the observed rating is a direct function of the operating and financial health of the issuer.

Next, several ratios had missing values and outliers which could disturb the regression output. These issues were encountered using the methodology described in Van Gestel et al. (2006). To deal with this, we started by replacing missing values of a variable with the median of all the companies in our sample. The outlier issue was addressed taking into account the fact that most independent variables were ratios and as such it could be expected that the distributions of these variables have fat tails with large positive and negative values. In order to prevent these outliers from having a negative impact on the model performance, the most extreme points were selected and reduced to the 3σ-borders in a robust way. For the limits we chose $m \pm 3\times s$, with m = median, s = IQR/ (2×0.6745) and IQR the interquartile range of the variable (Van Gestel et al., 2006).

The distributions of the different variables were analysed. If the distribution of a variable deviated considerably from a normal distribution, a logarithmic transformation ($x \rightarrow \log(1 + x)$) was used to see whether this led to a significant improvement of the final result. This was only the case for the sales variable.

2.3.2 The model

We have developed an internal credit rating model by estimating a logit and probit function. The dependent variable in our model is the external S&P rating, which we will try to replicate with our internal model. As the dependent variable in our model is an ordinal variable, an ordinal regression should be used (Allison, 1999). There are two main link functions that can be used in an ordinal regression to link the dependent variable with the independent variable. Both these functions will be tested in the regression: the logit function and the probit function which are based, respectively, on the logistic and normal density function. Logit and probit functions are very useful as their values are restricted to the interval between 0 and 1 and as such may be interpreted as probabilities. As our model will use financial ratios that are based on 3 years of data, looking at the input data, the developed model has a more hybrid, between point-in-time[32] and through-the-cycle, orientation.

The mathematical basis of the ordinal logistic regression is the following equation, which gives the cumulative probability of a rating i:

$$P(y \le i) = \frac{1}{1+\exp(-\theta_i + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)}, \text{ i=1,…,m}$$

with explanatory variables $x_1, x_2, \ldots, x_n$, the corresponding coefficients $\beta_1, \beta_2, \ldots, \beta_n$ and θ_i[33] a parameter linked to a category or in this case a rating i. The latent variable z gives a score for each company based on the independent variables and the coefficients (Van Gestel et al., 2006).

$$z = -\beta_1 x_1 - \beta_2 x_2 \ldots - \beta_n x_n$$

The score of a company can be used to determine the score of a company per category.

$$z_i = \theta_i - \beta_1 x_1 - \beta_2 x_2 \ldots - \beta_n x_n$$

or: $z_i = \log\left(\dfrac{P(y \le i)}{1 - P(y \le i)}\right)$

The score of a company per category can be used to calculate the cumulative probability of a certain category and the probability of a category.

$$P(y \le i) = \frac{1}{1 + e^{-z_i}}$$

$$P(y = i) = P(y \le i) - P(y \le i - 1)$$

In performing a regression, statistical software tools such as SPSS, STATA etc. will estimate the parameters $\theta_{1,\ldots,}\theta_m$ and $\beta_{1,\ldots}\beta_n$ using a maximum likelihood procedure that minimizes the negative log likelihood (NLL) (Van Gestel et al., 2006):

$$-\sum_{i=1}^{m} \log(P(y = i))$$

[32] A point-in-time (PIT) rating gives an indication of the borrower's current condition and/or most likely condition over a short chosen time horizon, typically one year.

[33] As $P(y \le m) = 1$, the parameter θ_m is equal to ∞.

Using probit as a link function could be a possible improvement to the model. Several default prediction models also incorporated probit as a link function (Moody's, 2000). The estimation procedure in general remains the same when using a probit link function. The probit function is the inverse cumulative distribution function of the standard normal distribution, which is a normal distribution with a mean of 0 and a standard deviation of 1.

Our goal is to build a simple, widely understood and easy-to-interpret model, with high accuracy and that is applicable to a large proportion of the European exposures that confront insurance companies. Quite a lot of models are built with information that is only available for a limited number of counterparties, so broad applicability is very important.

In order to arrive at the best model, we have applied three methods to select the significant variables (Garson, 2006). The first is backward regression where you start by incorporating all the possible explanatory variables into the regression. Then the least significant variable, the one with the highest p-value, is eliminated. This procedure is iterated until no variable meets the removal criterion, which in our case is a p-value higher than 0.05. The second, forward regression, implies that you start by incorporating one independent variable at a time. This is iterated until no more significant variables can be added to the model. The final method, stepwise regression, combines the previous methods. Variables that have been added in a prior phase can be removed later if they prove to be insignificant. This method normally gives the best results.

Furthermore, we also checked whether the coefficient of the variables had the right sign, implying that the sign corresponds to the expected sign from an intuitive economic point of view. Wrong signs can be due to bad data quality, spurious correlation or limited data. If a coefficient had a wrong sign, the variable was eliminated.

To guard against overfitting of data, we randomly divided our sample into two main sub-samples: the estimation sample and the hold-out sample. The in-sample was used to estimate our model; more specifically we used these observations to see what variables had a significant impact on the S&P rating and to estimate the corresponding coefficients. The model validation was done on the hold-out sample. For the observations in the hold-out sample we estimated the rating based on our internal model and compared the estimated rating to the assigned S&P rating. In the final regression the in-sample size was set at 70% of the total sample size. In order to build a performing model and to assure the model validation occurs correctly, it is important that the distribution of the ratings across both in- and out-of-sample is the same.

When building a model we should take into account the existence of different kinds of bias that will impact performance (Carey et al., 2001). As was pointed out earlier, we reduce potential bias and instability issues that might occur during the mapping procedure by combining the scoring and mapping in one exercise. In this way we try to address what is known as the 'informativeness bias', which is induced by the fact that S&P ratings are based on more information than the information that will be taken into account in an internal model. However, as we will never be able to perfectly replicate the S&P model, some bias will remain to exist. Another bias is the noisy-rating-assignment bias which is a kind of selection bias and results from the bucketing process intrinsic to rating assignments (Carey et al, 2001). We tackle this issue by keeping the initial S&P granularity, resulting in seventeen separate rating classes.

Both the informativeness bias and the noisy-rating-assignment bias are larger for grades that are further away from the average rating of the portfolio. Hence the largest deviation between predicted and actual ratings is expected for the lowest and highest grades. This is reinforced by what is known as the integer-problem, which occurs due to the hypothesis that each category is weighted by size. This statistical hypothesis maximises the final accuracy of the logit and probit model, but generates the integer-problem. Carey et al. (2001) show that the largest deviation between predicted and actual ratings can be expected for the grades with fewest observations. In our portfolio the highest exposure concentration appears in rating grades 8 and 9 and the lowest and highest rating grades have the fewest observations. As such the potential biases due to informativeness or noise might be intensified by the integer-problem. This issue will also be addressed when discussing the results.

2.4 Results

Of primary interest is the ability of the model to estimate ratings that are reasonably accurate copies of the external ratings both in- and out-of-sample. We start by discussing the in-sample performance of the model (see table 2.1). Both under the logit and probit model, six variables appear to be significant at 5% level[34]: Total liabilities/total assets (+)[35], EBITDA/sales (-), Return on assets (-), Sales (-), Country risk (+) and Industry classification (+). As was discussed earlier, previous studies have incorporated a wide range of variables as default predictors. The major strands of intuition that run through most of these studies are also reflected in our findings. Highly leveraged counterparts are more vulnerable to default because relatively modest fluctuations in value can cause insolvency. Moreover, companies having low EBITDA to sales ratios, a low return on assets, a poor recent cash

[34] We will only report the results for the logit model, as the probit model obtained essentially the same results.
[35] A positive sign implies that a higher financial ratio results in a higher model output, thus worse rating and a negative sign implies that a higher financial ratio results in a lower model output, thus better rating.

flow and/or returns are more vulnerable because earnings are autocorrelated. On the other hand large firms are less likely to default as they have more diversified resources and an easier access to capital markets. Also Country risk and Industry classification are significant variables in our model.

Insert Table 2.1 here

The estimated coefficients all have the correct estimated and economic significant sign. In logit and probit models, there is no natural magnitude for the linking variable, so we should be careful when interpreting the economic significance of the coefficients as such. However, what can be deducted from table 2.2 is that the likelihood ratio test rejects the hypothesis that all parameter coefficients are 0.

Insert Table 2.2 here

The Pseudo R^2-statistics show that a rather large part of the variation is explained by the model.

Insert Table 2.3 here

Even though these performance measures are rather abstract, they already indicate that the model performs well in-sample. However, in order to test the out-of-sample performance, other tests are required. In this paper the out-of-sample performance is first measured by notch difference graphs. A notch difference graph is a histogram showing cumulative accuracy for increasing notch differences between the S&P rating and the rating estimated by the model. The notch difference graphs depicted in figure 2.2 and 2.3 indicate that our model performs well both in-sample and out-of-sample. By several measures the model has been shown to outperform alternative models. Out-of-sample, almost 88 % of companies are classified correctly up to two notches of the real S&P rating.

Insert Figure 2.2 here

The cumulative percentage notch difference table (table 2.4) confirms the above. More than 85% of the companies are classified correctly up to two notches, implying that the bias in the estimates is rather limited. Further, Figure 2.3 confirms that our data are not being overfitted. Overfitting occurs when the modelling technique starts to fit the noise and/or idiosyncrasies in the training data. This typically leads to the out-of-sample performance being a lot more inferior than the in-sample performance. As Figure 2.3 illustrates, both in- and out-of-sample performance are very much in line, clearly demonstrating that overfitting is not an issue.

Insert Table 2.4 here

Insert Figure 2.3 here

The out-of-sample performance is also calculated using the correlation measures, Spearman's rho[36] and Kendall's tau[37]. Both statistics confirm our model performs well both in- and out-of-sample. The Kendall's tau correlations are situated at about 70% and are significant. The Spearman's rho correlations are situated at about 82% and also appear to be significant. The correlation measures also confirm that both the models perform in a quite similar way.

Insert Table 2.5 here

Insert Table 2.6 here

Based on the above results, we see that this simple model, only taking into account six very intuitive variables, performs very well both in- and out-of-sample. It is difficult to compare our findings with existing literature as most papers use a rating system with lower granularity by combining some of the original rating classes. So, even with a higher granularity and more rating classes, we still outperform most models. Therefore, our internal grades are very well quantified by our scoring model, which could imply that in our case the aforementioned biases are empirically irrelevant.

As mentioned before, this informativeness bias is potentially reinforced by the integer problem. We have investigated this issue in two ways. First we have calculated the average absolute mean difference per rating grade. Figure 2.4 confirms that the lowest deviations appear in the mid rating

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[36] The formula used to calculate the Spearman's rho coefficient is $r_s = 1 - \frac{6\sum_{i=1}^{N} d_i{}^2}{N(N^2-1)}$ where N is the sample size and d_i is the difference between the actual rating and the predicted rating.

[37] If there are N companies in a sample, then N(N-1)/2 pairs can be formed and Kendall's tau measures how many of these pairs are concordant (in same direction) and how many are discordant (in opposite direction). If the number of concordant pairs (=N_c) is higher than the number of discordant pairs (=N_d), the correlation is positive. Kendall's tau is defined by: $\tau = \frac{N_c - N_d}{N(N-1)/2}$ (Sheskin, 2000).

classes and the highest deviations appear in the tails with fewer observations. Second we have split the rating classes in a group of mid classes (1) and a group of tail classes (0) and calculated the difference between predicted and actual ratings for both groups. As is shown in table 2.7, the deviations are significantly lower for the mid classes as compared to the tails. This presents evidence of the integer problem. This is an important finding, especially taking into account that the exposures with the lowest number of observations are often the ones with the highest risk.

Insert Figure 2.4 here

Insert Table 2.7 here

2.5 Conclusion

Recently, the focus on risk management has increased dramatically. Because the insolvency of any financial intermediary might result in substantial losses with huge spill-over effects to different parts of the economy, this is especially true for financial institutions. In order to promote financial stability, regulatory authorities pay a lot of attention to setting minimum capital levels for different kinds of financial institutions. In line with the Basel II requirements for the banking industry, the European Commission has established the Solvency II Directive for insurance companies. One of the consequences of this planned reform will be a shift in focus to internal-based models for determining the minimum regulatory capital needed to cover unexpected losses. In the light of Solvency II, whose key objective for capital requirements is to better reflect the true risk of an insurance company, this paper seeks to develop a simple and intuitive credit rating model with a high degree of accuracy and reliability for the European corporate exposures of an insurance company. Taking into account the limited data and modelling experience of most insurance companies, combined with the fact that external ratings have proven to be a reasonably good indicator of corporate credit quality (e.g. Carey et al., 2001; Kao et al., 1990 etc), we suggest exploiting the expertise of external rating agencies by mimicking their ratings. Ratings are influenced by the data they are based on. Carey et al. (2001) point out that parameterization of credit risk models using ratings is risky, but that the risks are controllable by careful analysis and management.

It is often argued that internal rating systems differ a lot from the systems used by external agencies and that, as a result, the mapping becomes unstable. By combining credit scoring and mapping in one exercise, we have addressed some of the potential biases and instability issues that might arise.

After thorough analysis, we found a logit model including six variables: Sales (negative impact), EBITDA/sales (negative impact), Return on assets (negative impact), Total liabilities/total assets (positive impact), Country risk (positive impact) and Industry classification (positive impact). The major strands of intuition that run through most of previous academic literature are also confirmed in this paper. However, using several measures, the model proves to outperform alternative models. Out-of-sample, almost 88% of companies are classified correctly up to two notches of the real S&P rating. Besides its accuracy, the model proves easy to use and to apply. Quite a lot of models have been built with information that is available for only a limited number of counterparties, requiring broad applicability to be set as an important characteristic of our model.

2.6 References

Allison P., 1999. Logistic regression using SAS: theory and Application. SAS Press.

Altman E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance 23, 589-609.

Altman E.I., Haldeman, R. Narayanan, P., 1977. Zeta analysis: a new model to identify bankruptcy risk of corporations. Journal of Banking & Finance 1, 29-54.

Altman E.I., 1989. Measuring corporate bond mortality and performance. Journal of Finance 44, 909-922.

Altman, E.I., Marco, G. ,Varetto, F. 1994. Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks (The Italian Experience). Journal of Banking & Finance, Vol. 18, 505-529.

Altman, E.I., Narayanan, P. 1997. Business Failure Classification Models: An International Survey. In: Choi, F. (Ed.), International Accounting, 2nd ed. Wiley, New York.

Altman E., Saunders A., 1998. Credit risk measurement: developments over the last 20 years. Journal of Banking & Finance 21, 1721-1742.

Altman, E.I., Suggitt H., 2000. Default rates in the syndicated bank loan market: a mortality analysis. Journal of banking & Finance 24, 229-254.

Altman, E.I., Rijken, H.A., 2004. How rating agencies achieve rating stability. Journal of Banking and Finance 28, 2679-2714.

Altman, E., Wilson, N., Sabato, G., 2009. The value of qualitative information in SME risk assessment. NY Stern Working Paper.

Amato, J.D., Furfine C.H., 2004. Are credit ratings procyclical? Journal of Banking & Finance, 28, 2641-2677.

Ang J.S., Patel K.A., 1975. Bond rating methods: comparison and validation. Journal of Finance 30, 631-640.

Balcaen S., Ooghe H., 2004. 35 years study on business failure: an overview of the classic statistical methodologies and their related problems. Vlerick working paper.

Barniv, R., Hershbarger, R.A., 1990. Classifying financial distress in the life insurance industry. Journal of Risk and Insurance 57, 110-136.

Barniv, R., McDonald J.B., 1992. Identifying financial distress in the insurance industry: a synthesis of methodological and empirical issues. Journal of Risk and Insurance 59, 543-574.

Beaver W.H., 1966. Financial ratios as predictors of failure. Journal of Accounting Research 4, 71-111.

Beltratti, A., Giuseppe, C., 2008. Why are insurance companies different? The limits of convergence among financial institutions. The Geneva Papers 33, 363-388.

Berger, L.A., Cummins, J.D., Tennyson, S., 1992. Reinsurance and the liability insurance crisis. Journal of Risk and Uncertainty 5, 253-272.

Beynon, M.J., 2005. Optimizing object classification under ambiguity/ignorance: application to the credit rating problem. Intelligent systems in Accounting, Finance and Management, 13, 113-130.

Black F., Scholes M., 1973. The pricing of options and corporate liabilities. Journal of Political Economy 81, 637-659.

Blume M., Lim F., Mackinlay C., 1998. The declining credit quality of U.S. corporate debt: myth or reality. The Journal of Finance LIII, 1389 – 1413.

Brockett P., Golden L., Jang J., Yang C., 2006. A comparison of neural network, statistical methods, and variable choice for life insurers' financial distress prediction. Journal of Risk and Insurance 73, 397-419.

Brunner, A., Krahnen, J. P., Weber, M. 2000. Information production in credit relationships: On the role of internal ratings in commercial banking. Center for Financial Studies Working Paper No. 2000/10.

Bunn. P., Redwood, V., 2003. Company accounts based modelling of business failures and the implications for financial stability. Bank of England working paper, No. 210.

Cantor R., Packer F., 1996. Determinants and impact of sovereign credit rating. Federal Reserve Bank of New York Economic Policy Review, October 1996, 1-15.

Carey, M., Hrycay, M. 2001. Parametrizing credit risk models with rating data. Journal of Banking & Finance 25, 197-270.

Chava, S., Jarrow, R. 2004. Bankruptcy Prediction With Industry Effects. Review of Finance 8, 537 – 569.

Chaveesuk R., Srivaree-Ratana C., Smith A.E., 1999. Alternative neural networks approaches to corporate bond rating. Journal of engineering-valuation and cost analysis 2, 117-131.

Chorafas D.N., 2004. Operational risk control with Basel II. Basic principles and capital requirements. Elsevier, Amsterdam.

Coats K.P., Fant L.F., 1993. Recognising financial distress patterns using neural network tool. Financial Management 22, 142-155.

Crouhy, M. Galai, D., Mark, R., 2001. Parametrizing credit risk models with rating data. Journal of Banking & Finance 25, 47-95.

Daubie M., Levecq Ph., Meskens N., 2002. A comparison of the rough sets and recursive partitioning induction approach: an application to commercial loans. International Transactions in Operational research 9, 681-694.

Eling M., Schmeiser H., Schmit J.T., 2007. The Solvency II process: overview and critical analysis. Risk Management and Insurance Review (10/1).

English,W.B., Nelson,W.R., 1998. Bank Risk Rating of Business Loans. Working Papers: Finance & Economics Discussion Series, Board of Governors of the Federal Reserve System.

Eurostat, 2008. General Economic Background.
http://epp.eurostat.ec.europa.eu/portal/page?_pageid=1996,45323734&_dad=portal&_schema=PORTAL&screen=welcomeref&open=/&product=STRIND_ECOBAC&depth=2

Estrella, A., Park, S., Peristiani, S., 1999. Capital ratios and credit ratings as predictors of bank failures. WP, Federal Reserve Bank of NY

Fantazzini, D., Figini, S., 2009. Random survival forest models for SME credit risk measurement. Methodology and Computing in Applied Probability 11, 29_45.

Fernandes J.F., 2005. Corporate credit risk modeling: quantitative rating system and probability of default estimation. Banco BPI, April 2005.

Florez-Lopez R., 2007. Modelling of insurers' rating determinants. An application of machine learning techniques and statistical models. European Journal of Operational Research 183, 1488-1512.

Frydman H., Altman E.I., Kao D.L., 1985. Introducing recursive portioning for financial classification: the case of financial distress. Journal of Finance 40, 269-291.

Garson, G. D. 2006. Logistic Regressin. Statnotes: Topics in Multivariate Analysis.

Gaver, J.J., Pottier, S.W., 2005. The role of holding company financial information in the insurer-rating process: evidence from the property-liability industry. The Journal of Risk and Insurance 72, 77-103.

Grunert, J., Norden L., Weber M, 2005. The Role of Non-Financial Factors in Internal Credit Ratings. Journal of Banking & Finance 29, 509-53.

Hand, J.R.M., Holthausen, R.W., Leftwich, R.W. 1992. The Effect of Bond Rating Agency Announcements on Bond and Stock Prices. The Journal of Finance 67, 733-752.

Hickman, W. B., 1958. Corporate bond quality and investor experience. Princeton University Press.

Hill, P and Wilson N., 2007, Predicting the corporate failure of unlisted companies. Working paper, CMRC, Leeds University.

Hillegeist, S.A., Keating E.K., Cram D.P., Lundstedt K.G., 2004. Assessing the probability of bankruptcy. Review of Accounting Studies 9, 5-34.

Hol, S., 2006. The influence of the business cycle on bankruptcy probability. WP.

Horrigan, J.O. 1966. The determination of long-term credit standing with financial ratios. Journal of Accounting Research 4, 44-62.

Jankowitsch R., Pichler S., Schwaiger W., 2007. Modelling the economic value of credit rating systems. Journal of Banking & Finance 31, 181-198.

Kaplan, R., Urwitz, G., 1979. Statistical Models of Bond Ratings: A Methodological Enquiry. Journal of Business 52, 231-261.

Katz, S., 1974. The price and adjustment process of bonds to rating reclassifications: a test of bond market efficiency. The Journal of Finance 29, 551-559.

Kao C., Wu C., 1990. Two-step estimation of linear models with ordinal unobserved variables: the case for corporate bonds. Journal of business & economic statistics 8, 317-325.

Krahnen J.P., Weber M., 2001. Generally accepted rating principles: a primer. Journal of Banking & Finance 25, 3-23.

Lane W.R., Looney S.W., Wansley J.W., 1986. An application of the Cox proportional hazards model to bank failure. Journal of Banking & Finance 10, 511-531.

Mayers. D., C. Smith C., 1990. On the corporate demand for insurance: evidence from the reinsurance market. Joumal of Business 63, 19-40.

Merton, R. 1974. On the pricing of corporate debt. Journal of Finance 29, 449-470.

Metz, A., Cantor, R., 2006. Moody's credit rating prediction model. Moody's Investors Service, November 2006.

Moody's, 2000. Riskcalc for private companies: Moody's default model. Moody's Investor Service, May 2000.

Moody's, 2006. The distribution of common financial ratios by rating and industry for North American non-financial corporations, July 2006.

Ohlson, J. 1980. Financial ratios and the probalistic prediction of bankruptcy. Journal of Accounting Research 18, 109-131.

Ooghe H., Spaenjers C., Vandermoere P., 2005. Business failure prediction: simple-intuitive models versus statistical models. Vlerick Working Paper.

Peel, M.J., Peel, D.A., and Pope, P.F. 1986. Predicting corporate failure – Some results for the UK corporate sector. Omega International Journal of Management Science 14, 5-12.

Peel, M.J., Peel, D.A., 1988. A multi-logit approach to predicting corporate failure- Some evidence for the UK Corporate Sector. Omega International Journal of Management Science 16, 309-318.

Pinches, G.E., Mingo, K.A., 1973. A multivariate analysis of industrial. bond ratings, Journal of Finance 28, 1-18.

Pinches, G.E., Mingo, K.A., 1975. The role of subordination and industrial bond ratings. Journal of Finance 30, 201-206.

Platt, H.D., Platt, M., 1991. A note on the use of industry-relative ratios in bankruptcy prediction. Journal of Banking & Finance 15, 1183-1194.

Pogue, T., Soldofsky, R., 1969. What is in a bond rating? Journal of Financial and Quantitative Analysis 4, 210-228.

Santomero A., Vinso, J., 1977. Estimating the probability of failure for firms in the banking system. Journal of Banking & Finance 1, 185-206.

Sheskin, D., 2000. Handbook of parametric and nonparametric statistical procedures, second edition. Chapman & Hall.

Scott, J. 1981. The probability of bankruptcy: a comparison of empirical predictions and theoretical models. Journal of Banking & Finance 5, 317-344.

Standard & Poor's, 2002. Standard& Poor's Corporate ratings Criteria.

Shumway, T., 2001. Forecasting bankruptcy more accurately: a simple hazard model. Journal of Business 74, 101-124.

Stickney C.P. , Brown P.R., Wahlen J.M., 2006. Financial reporting, financial statement analysis and valuation. Thomson South-Western.

Tabakis, E., Vinci, A., 2002. Analyzing and combining multiple credit assessments of financial institutions. WP No 123, European central Bank.

Tamari M., 1966. Financial ratios as a means of forecasting bankruptcy. Management International Review 4, 15-21.

Tiller J.E. Jr., Tiller D.F., 1995. Life, health & annuity reinsurance, Second Edition, ACTEX Publications Inc.

Treacy, W.F., Carey, M.., 1998. Credit risk rating at large US banks. Federal Reserve Bulletin, Nov.

Trieshmann, J.S., Pinches, G.E., 1973. A multivariate model for predicting financially distressed P-L insurers. The Journal of Risk and Insurance 40, 327-338.

Van Gestel T., Baesens B., Van Dijcke P., Suykens J.A.K., Garcia J., Alderweireld T., 2005. Linear and nonlinear credit scoring by combining logistic regression and support vector machines. Journal of Credit Risk 1.

Van Gestel T., Baesens B., Van Dijcke P., Garcia J., Suykens J.A.K , Vanthienen J., 2006. A process model to develop an internal rating system: sovereign credit ratings. Decision Support Systems 2, 1131-1151.

Van Gestel T., Baesens B., 2009. Credit risk management: basic concepts: financial risk components, rating analysis, models, economic and regulatory capital. Oxford University Press.

West, R.R., 1970. An alternative approach to predicting corporate bond ratios. Journal of Accounting Research 7, 118-127.

West, R. C. 1985. A factor-analytic approach to bank condition. Journal of Banking & Finance 9, 253-266.

Wilcox, J.W. 1973. A prediction of business failure using accounting data. Journal of Accounting Research: selected studies , 164-179.

Wilson, N., Altantlar, A., Hill, P., 2009. Insolvency risk models for non-listed companies. Working paper

Yang Z.R., Platt M.B., Platt H.D., 1999. Probabilistic neural networks in bankruptcy prediction. Journal of Business Research 44, 67-74.

Zavgren, C.V., 1985. Assessing the vulnerability to failure of American industrial firms: a logistic analysis. Journal of Business Finance and Accounting 12, 19-45.

Appendix

Appendix 2.1: Independent variables

Variable	**Explanation**
Financial variables	
Profitability:	
EBITDA/sales	a profitability measure describing the amount of EBITDA which is generated per € of sales.
Net Return On Assets	a profitability measure describing the ability to generate earnings independent of the financing of the assets
Net return on equity after taxes	a profitability measure describing the return to shareholders
Asset turnover	a profitability and efficiency measure describing the rate at which the total amount of assets turn over
Fixed assets turnover	a profitability and efficiency measure describing the rate at which fixed assets turn over
Profit margin for ROA	a profitability measure describing the amount of profit that is generated per amount of sales
Liquidity:	
Accounts receivable turnover	a liquidity and efficiency measure describing the rate at which accounts receivable turn over
Stock turnover	a liquidity and efficiency measure describing the rate at which inventories turn over
Working capital/sales	a productivity ratio which is the inverse of working capital productivity (the lower, the better)
(Cash + Short term investments – financial debt)/current assets	a liquidity ratio describing the relative net amount of the most liquid assets
Current ratio	a liquidity measure describing the amount of current assets relative to current liabilities
Quick ratio	a liquidity measure similar to the current ratio, but which eliminates the least liquid asset (inventories) from current assets
Revenues/cash	a liquidity measure which can also be viewed as a cash turnover ratio
Solvency:	
Self-financing level	a solvency measure describing the past profitability of a company (accumulated profit and retained earnings/total assets)
EBITDA/interest expense	a solvency measure describing the extent to which EBITDA covers interest expense (an interest coverage ratio)
Short term financial debt level	a solvency ratio describing the relative amount of short term financial debt in the total amount of short term debt

Cash flow after taxes / liabilities	a solvency ratio describing the extent to which the cash flow covers the total amount of a company's liabilities
Net Interest Bearing Debt/Net worth	a solvency measure describing the relative amount of financial debt outstanding
General level of financial independence	a solvency measure describing the amount of shareholder's equity relative to the sum of shareholder's equity and liabilities
Total liabilities/total assets	a solvency measure that is often referred to as the financial leverage of a company
Added value::	
Gross added value/personnel	a measure describing the added value generated per employee
Size variables	
Sales	a variable that is linked to the size of a company
3 year trend of sales	a measure describing the relative trend in sales over the last three years
Common equity	a variable that is linked to the size of a company and that is also indirectly linked to the leverage of a company
Other variables	
S&P sovereign credit rating	an indicator for country risk
Industry Classification	an indicator for the industry based on the Global Industry Classification Standards

Appendix 2.2: Output K-means clustering

Case Number	VAR00001	Cluster	Distance
1	Aerospace	2	1.533
2	Automotive	1	1.361
3	Chemical	3	1.398
4	Construction	1	1.615
5	Consumer Prod	3	2.214
6	Energy and Environment	2	1.507
7	Healthcare	1	2.429
8	Leisure	3	.848
9	Manufacturing	3	2.021
10	Media	3	.987
11	Metals and Mining	1	2.272
12	Natural Prod	3	1.098
13	Oil and Gas	4	0.000
14	Packaging	3	1.055
15	Pharmaceuticals	3	2.162
16	Retail and Distribution	2	.740
17	Services	3	1.405
18	Technology	1	1.584
19	Telecomm	2	1.424
20	Transport	3	2.054

Cluster membership

Tables

	Estimates	Std. error	Wald	Df	Sig	95% CI Interval	
						Lower Bound	Upper Bound
Treshold per rating							
1	-21.562	2.15	100.6	1	0	-25.78	-17.35
2	-21.094	2.109	100.08	1	0	-25.23	-16.96
3	-20.736	2.086	98.829	1	0	-24.82	-16.65
4	-20.021	2.053	95.11	1	0	-24.05	-16.00
5	-18.857	2.011	87.932	1	0	-22.80	-14.92
6	-17.886	1.978	81.771	1	0	-21.76	-14.01
7	-16.691	1.94	73.991	1	0	-20.50	-12.89
8	-15.267	1.902	64.451	1	0	-18.99	-11.54
9	-14.097	1.867	56.995	1	0	-17.76	-10.44
10	-13.286	1.839	52.191	1	0	-16.89	-9.68
11	-12.695	1.816	48.854	1	0	-16.26	-9.14
12	-12.077	1.791	45.46	1	0	-15.59	-8.57
13	-10.846	1.741	38.794	1	0	-14.26	-7.43
14	-9.725	1.712	32.282	1	0	-13.08	-6.37
15	-8.245	1.705	23.375	1	0	-11.59	-4.90
16	-6.585	1.775	13.757	1	0	-10.07	-3.11
Location							
Sales	-2.695	0.265	103.26	1	0	-3.22	-2.18
Ebitda/sales	-6.477	1.268	26.113	1	0	-8.96	-3.99
ROA	-0.15	0.027	31.473	1	0	-0.20	-0.10
Liab/TA	3.278	0.825	15.769	1	0	1.66	4.90
Country risk				1	0.00		
	0.228	0.071	10.341	1	1	0.09	0.37
Industry 2	3.244	0.533	37.057	1	0	2.20	4.29
Industry 3	2.344	0.583	16.154	1	0	1.20	3.49
Industry 4	3.338	0.553	36.371	1	0	2.25	4.42
Industry 5	2.384	0.611	15.241	1	0	1.19	3.58
Industry 6					0.00		
	3.397	1.064	10.193	1	1	1.31	5.48
Industry 7	0	.	.	0	.	.	.
Industry 8	5.093	0.886	33.036	1	0	3.36	6.83
Industry 9	3.646	0.644	32.019	1	0	2.38	4.91
Industry 10	0	.	.	0	.	.	.

Table 2.1: Parameter estimates logit

	Logit	
	Intercept only	***Final***
-2 log Likelihood	953.783	718.464
Chi-square		235.319
Df		12
P-value		< 0.001

Table 2.2: Likelihood ratio test for logit model

Pseudo R^2	**Logit**
Cox and Snell	0.71
Nagelkerke	0.715
McFadden	0.247

Table 2.3: Pseudo R^2-statistics for logit model

Logit	
0 notches	25.30%
1 notch	63.86%
2 notches	87.95%
3 notches	93.98%
4 notches	97.59%
5 notches	100.00%
6 notches	100.00%
7 notches	100.00%

Table 2.4: Out-of-sample cumulative % notch difference table for logit model

		Logit
Kendall's Tau	Correlation	0.710
	P-value	< 0.001
Spearman's Rho	Correlation	0.828
	P-value	<0.001

Table 2.5: In-sample correlation measures for logit

		Logit
Kendall's Tau	Correlation	0.689
	P-value	0.000
Spearman's Rho	Correlation	0.821
	P-value	0.000

Table 2.6: Out-of-sample correlation measures for logit

Classif		absdiff	diff
Tails	Mean	2.11	0.16
	N	37	37
	Std. Deviation	1.52	2.62
Midclass	Mean	1.40	-0.16
	N	45	45
	Std. Deviation	1.34	1.94
Total	Mean	1.72	-0.01
	N	82	82
	Std. Deviation	1.46	2.26

Table 2.7: The mean absolute difference between the predicted and actual rating per rating group

Figures

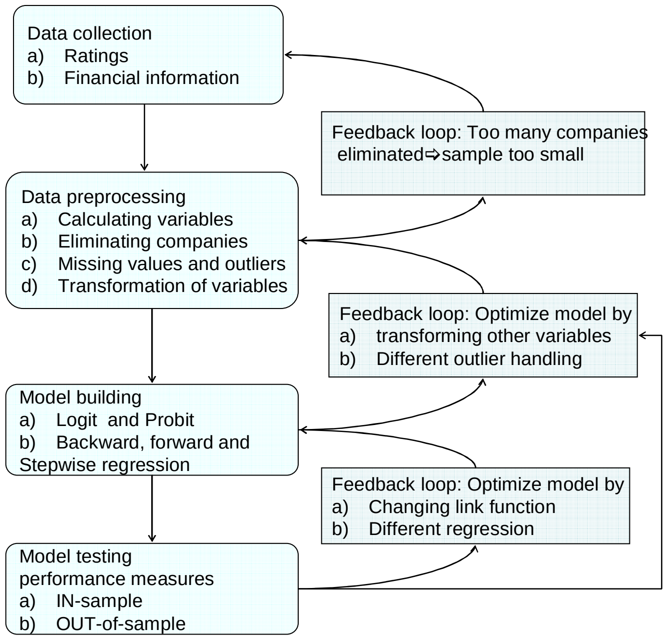

Figure 2.1: The modelling approach

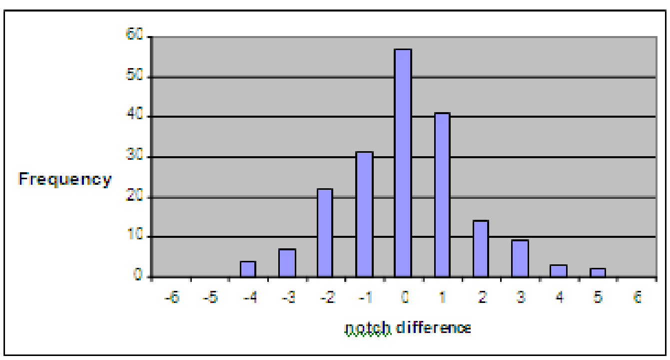

Figure 2.2: Out-of-sample notch difference graph for logit model

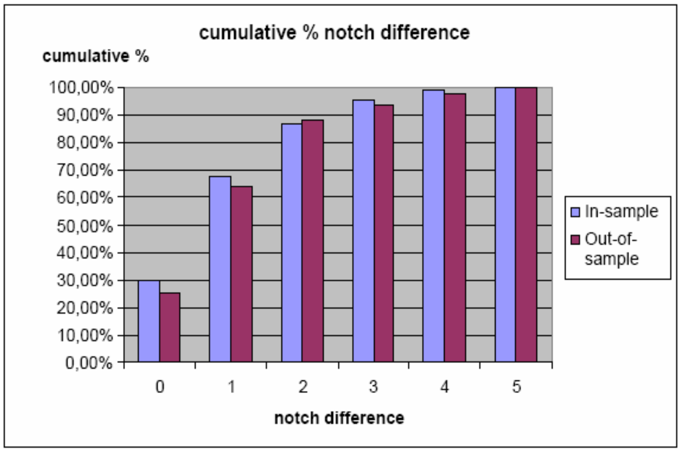

Figure 2.3: Cumulative % notch difference graph for logit model

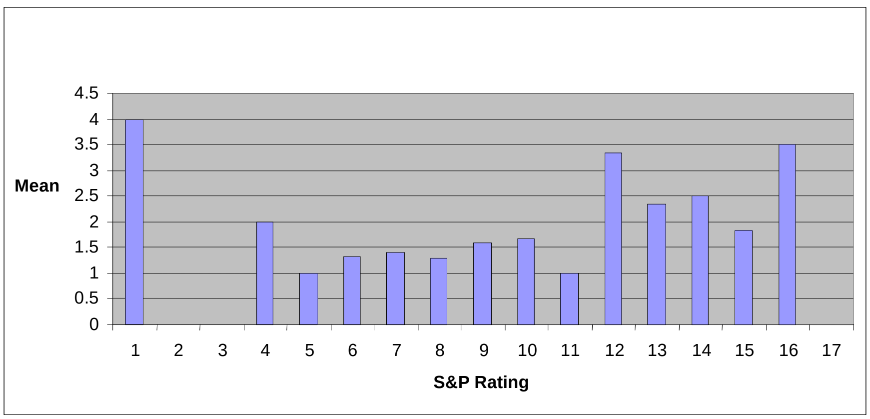

Figure 2.4: The absolute mean difference between the predicted and actual rating per rating class

"Sovereign risk has supplanted regulatory risk as the primary focus of bank bondholders. Steep downgrades of the sovereign-debt ratings of countries such as Portugal, Greece and Ireland would probably translate into immediate rating cuts for their banks". The Economist – February 11, 2010.

Chapter 3: Analyzing bank ratings: key determinants and procyclicality*

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Abstract

This paper presents a joint examination of how different factors influence the assignment of S&P and Moody's long term bank ratings using a unique data set covering different regions, bank sizes, and bank types. In doing so, we include new bank and country specific variables. Furthermore, we include measures of the business cycle in our analysis to determine whether long term bank ratings tend to be related to the cycle after conditioning on a set of variables. Using annual data on US and European banks rated by S&P and/or Moody's, we find that the bank ratings of both agencies exhibit a different sensitivity to the business cycle. Finally, we will check our findings on a sample of banks that are rated by both rating agencies while controlling for potential sample selection bias.

* This paper benefited from numerous comments and suggestions received at the EURO conference on Operational Research EURO XXIV (Lisbon, 2010).

3.1 Introduction

Due to increasing deregulation and globalization from the eighties onwards, the banking system has become more vulnerable and banking crises have increased, causing and exacerbating economic downturns (Demirguc-Kunt et al., 2008). This vulnerability and the negative impact on financial stability were felt in the latest financial crisis. As a result many authorities are currently upgrading banking regulation and supervision in order to prevent future crises (e.g. De Larosière report, 2009). One of the challenges in this process is induced by the fact that risks taken in the process of financial intermediation are hard to observe and assess from outside the bank. In the absence of tight regulation, this opaqueness exposes banks to runs and systemic risk. In order to reduce this lack of transparency, credit rating agencies (CRAs) such as S&P, Fitch and Moody's provide information that can help various stakeholders to evaluate the credit risk of issues and issuers.

For many observers of financial markets, credit ratings appear to play an essential role as an independent and objective measure of credit quality. A significant proportion of debt issuers believe that having an external rating is indispensible for an issuer to attract investors in international capital markets (Poon et al., 2005). Over the past decade, ratings have gained further importance due to Basel II, the development of advanced credit risk models, their use in structured finance etc. (Altman et al., 2002; Carey et al., 2001; Saunders, 2002; Van Gestel et al., 2005, 2009). As such, a careful understanding of the determinants of ratings and the comparability of different rating agencies' ratings and methodologies is becoming ever more important (e.g. Baker and Mansi, 2002).

Moreover, in recent years negative publicity (e.g. Vink et al., 2009) has drawn attention to CRAs whose expertise and independence are both under attack. Since the 2008 crisis the credibility of credit ratings as indicators of credit risk has diminished, calling into question the merit of using these ratings in future analysis. However, it should be noted that the latest stricture on rating agencies has mainly focused on ratings of structured products (see Demirguc-Kunt and Detragiache, 2010). Nonetheless, in the past the role of CRAs has frequently also been questioned (e.g. Altman and Saunders, 2001; Altman et al. 2002). One important argument against external ratings is the fact that there is no explicit guarantee that external rating agencies can assess credit risk better than banks themselves. Altman and Saunders (2001) argue for instance that agency ratings information could be misleading since their analysis is backward rather than forward looking. The low transparency in the rating assignments also contributes to this critique. At the same time the users of ratings are also to blame. Uncritically adopting ratings is insufficient if they want to make the right decisions.

The fact that credit rating agencies do not find it that easy to evaluate credit risk either seems especially true in the case of banks. Morgan (2002) shows that Moody's and S&P have more split ratings over financial intermediaries, suggesting that banks are more difficult to rate because of their opaqueness. This additional lack of transparency is linked to the bank's asset base and its high leverage, which create agency problems and further increase uncertainty over its assets.

So far the research linked to ratings of financial institutions is rather limited. We will fill this gap by investigating the key determinants driving long term (LT) bank ratings, using a unique dataset of Moody's and S&P covering the period from 2000 to 2009. The first step in understanding ratings is to analyze the rating determinants. As such, based on a literature review of bank ratings and insights from corporate rating literature we will investigate the key factors driving long term bank ratings. Furthermore, we will examine the importance of the country environment on bank ratings. The need for this cross-country analysis is induced by globalization and the fact that financial institutions are expanding more than ever beyond their home country. Fons (1998) and Demirguc-Kunt et al. (2008) show that there is a link between credit ratings on the one hand and accounting standards, supervision and disclosure requirements on the other hand. Using additional variables, we will investigate whether these findings also hold for our LT bank rating sample.

Credit rating agencies claim that ratings are the outcome of a through-the-cycle methodology which makes them stable and insensitive to temporary credit risk fluctuations. As such credit ratings incorporate permanent credit risk components and rating agencies follow prudent migration policies (Cantor and Mann, 2003a). However, even though one of the main goals of CRAs is to provide ratings that are insensitive to cyclical evolution, there is evidence that in reality this is not the case (e.g. Altman and Kao, 1992; Amato and Furfine, 2004; Cantor and Mann, 2003b; Nickell et al. 2000). This phenomenon, called 'procyclical behaviour' might have a major impact on financial stability. As such we will also investigate the impact and causes of temporal effects on bank credit ratings.

As will be discussed in the literature review, previous papers in bank rating literature mainly rely on the bank rating data of only one rating agency, arguing that the results will easily hold for the others as well (e.g. Poon et al., 1999 based on Moody's; Poon, 2003a based on S&P; Poon, 2003b based on Fitch; Van Roy, 2006 based on Fitch). Furthermore, despite the fact that some agencies systematically assign higher ratings than others, various bank stakeholders tend to implicitly assume that the different Nationally Recognized Statistical Rating Organizations (NRSROs)[38] have equivalent rating scales. In this paper we will assess the appropriateness of this assumption for banks. In our sample, for example, Moody's assigns lower - thus more favourable - bank ratings on average than S&P (see Table 3.1[39] and Table 3.2). As suggested by Morgan (2002), rating agencies rely on extensive industry-specific knowledge, so it seems likely that the expertise and rating performance of rating agencies varies across

[38] A Nationally Recognized Statistical Rating Organization (NRSRO) is a credit rating agency which issues ratings that are recognized by the U.S. Securities and Exchange Commission (SEC) for certain regulatory purposes.
[39] For the full sample this holds, with the exception of the year 2009 where the opposite is true.

industries, which is confirmed by the high number of split ratings for financial institutions. Furthermore the rating process and methodology also vary widely across CRAs. Some authors recognize the prevalent differences and explicitly state that their research outcome does not necessarily hold for the CRAs that were not presented in the sample (e.g. Amato and Furfine, 2004). This is an important issue especially for regulatory and supervisory purposes and has already been addressed in the corporate rating literature (e.g. Cantor and Packer, 1997) and for insurance companies (Pottier and Sommer, 1999) but has to our knowledge not been examined for LT bank ratings.
In addition, it is also important to understand why a bank would opt to be rated by two rating agencies. Even though a lot of banks ask for a rating from at least one rating agency, this is voluntary and only some apply for a second rating. In our sample 14.3% of S&P rated banks received a Moody's rating in December 2009 and 49.8% of Moody's rated banks received an S&P rating in December 2009. Taking into account the high number of split ratings for banks; it is particularly interesting to explore the motives for obtaining additional ratings. Furthermore, it is important to be aware of the differences in bank ratings between rating agencies. Besides the source of the differences it is also interesting to see whether differences in ratings appear to be random or systemic and to understand whether disagreements in ratings are driven by differing rating models or whether they are a result of selection bias. If all banks were rated by both agencies, differences in average rating could be perceived as differences in rating scale. However, not all banks are rated by Moody's and S&P, so differences could be an indication of sample selection (see Cantor and Packer, 1997).

This paper shows that Moody's and S&P have different rating determinants, different sensitivity towards the business cycle and behave differently when rating banks that are rated by both of them.

In academic literature, papers on credit ratings clearly focus on corporate ratings, often excluding banks and other financial institutions from their sample. As such, this article makes a significant contribution to the literature on bank ratings both from a policy and an academic perspective. Bank ratings hold a key position in today's financial markets, where high-quality, widely recognised ratings are a basic condition for a financial market to function properly. CRA's rating reports often provoke comments from regulators, politicians and the business community. Furthermore, a rating change influences stock and bond prices and, more generally the terms at which funding can be attracted (e.g. Baker and Mansi, 2002, Liu et al., 1999). Due to their opaqueness, the role of ratings is especially crucial for banks. The current regulatory and macro-economic environment that is characterized by debates on higher capital ratios, stress tests etc., make it even more relevant to understand the way bank ratings are determined and how they differ across rating agencies.

In the next section of this paper, we will discuss the relevant literature covering credit ratings in general and, specifically bank ratings. Next, we will set out the data, empirical strategy and model estimations. Finally we will present the results, including diagnostic tests of model performance.

3.2 Literature review

Bank ratings are vitally important to various stakeholders. Strong financial ratings give banks higher access to capital markets at better conditions and will directly influence bank operations and performance.

At the same time these ratings are a valuable tool for depositors, debtors, regulators etc. in assessing the financial strength of the bank. Both Moody's and S&P have a long history in rating banks. S&P issued its first bank rating in June 1947 and by December 2009 it was rating about 2606 banks globally using an AAA-through-D scale. Even though Moody's only issued its first bank rating in July 1973, by December 2009 this CRA was rating over 1024 banks globally using an Aaa-through-C scale. To form their rating opinion, both agencies rely on a broad range of business and financial attributes[40] that could influence the banks' creditworthiness.

Likewise in the academic world, a significant strand of research has examined credit risk modelling and credit rating determinants. Over the past 40 years, there has been an ongoing search to find the ultimate credit risk measures and models. As a result there have been major developments in techniques, explaining variables, datasets and in the number and type of events that are being modelled. The existing literature can be divided into different strands. An important category relates to the determinants of ratings. One series of papers in this category investigates whether ratings measure what they are supposed to measure (Ang and Patel, 1975; Kao et al., 1990) and finds that ratings do have an informational content. Secondly there are papers investigating whether ratings convey information that is not reflected in asset prices, in which mixed results have been obtained up to now (Hand et al., 1992; Katz, 1974). Thirdly, there are various papers investigating the information that is reflected in ratings. These papers can be divided based on the methodology that is used and on the independent variables that are investigated (e.g. Altman, 1989; Altman and Katz, 1976; Amato and Furfine, 2004; Blume et al., 1998; Crouhy et al., 2001; Ohlson, 1980 etc.).

In 1968, Altman used Multiple Discriminants Analysis to explain the difference between US solvent and insolvent corporates using 5 financial and accounting variables. Building on this pioneering study Altman and others have further refined bankruptcy models (e.g. Ohlson, 1980; Zavgren, 1983 etc.). Horrigan (1966) was the first to estimate and predict corporate bond ratings based on the financial

[40] Business attributes include factors such as country risk, environment, company position, geographical diversification and management strategy. The financial attributes include risk management, capitalization, earnings, funding and liquidity, accounting and governance.

ratios of the rated company and characteristics of the bond. Since then, many others have developed bond rating models (Brister et al., 1994; Ederington and Yawitz 1987; Gentry et al., 1988; Kaplan and Urwitz, 1979; Pinches and Mingo, 1973, 1975). In a later stage academics have also explored alternative ways to address failure prediction and credit risk modelling such as machine learning, survival analysis and neural networks (e.g. Beynon et al., 2005, Chaveesuk R. et al., 1999; Daubie et al., 2002, Florez-Lopez, 2007; Lane et al., 1986; Yang et al., 1999). In some circumstances these expert system methods can out-perform MDA and logit analysis (Brockett et al., 2006 and Coats and Fant, 1993). However, notwithstanding the fact that, for instance, neural networks are able to discriminate patterns that are not necessarily linearly separable, the often large number of parameters that are involved in a neural model cause generalization problems and make these models true black-boxes.

Looking at the variables that have been investigated, a first set of explanatory variables is more quantitative by nature and includes variables such as profitability, liquidity, interest coverage, industry etc. (Amato and Furfine, 2004; Blume et al., 1998; Estrella et al., 1999; Tabakis et al., 2002). Early studies (e.g. Horrigan, 1966; Pinches et al., 1975; Pogue et al., 1969) already found that financial data are a key input for corporate bond ratings. Later more qualitative variables were also added to the analysis: age, type of business and industry (e.g. Altman et al., 2009; Chava et al., 2004; Platt and Platt, 1991) along with the inclusion of macro-economic indicators (Hol et al., 2006; Wilson et al., 2009).

Throughout all these studies there has been a clear focus on US corporate bonds. Only a fraction of the research in this area deals with bank ratings. However, it should be noted that long term bank ratings are quite different from corporate bond ratings. For one thing, a bond rating applies to a specific issue, whereas a bank rating applies to the financial institution itself. Furthermore a bond has fixed time payments and bank obligations are uncertain in timing and amount. Also the specific asset and liability structure and the regulations with which banks should comply make them quite different entities from corporates. Another important distinction is that there appears to be less convergence of opinion among CRAs when it comes to banks (Morgan, 2002).

In addition, the existing focus in literature on US also has its limitations. The credit risk rating literature concerning European exposures is rather limited. However, existing differences between the two markets might undermine the extrapolation potential to a European environment. This is especially true for banks that operate in quite different environments with respect to regulation, supervision, safety nets etc. As such, we feel it is necessary to include both US and European banks in our sample.

In the next paragraphs we will discuss the most important research that has already been done. To our knowledge the existing studies on bank ratings are quite different from this paper as they analyze bank financial strength ratings (BFSR) rather than long term bank ratings, they tend to include only traditional financial health measures , they rely solely on data from one rating agency or they have a cross sectional setting. None of the existing studies include information for the years 2008 and 2009, however given the banking crisis during these years, including them may shed new light on existing research and/or provide new insights.

Poon et al. (1999) use a logit model to investigate Moody's BFSR. In their model they include traditional variables related to risk, loan provisioning and profitability and show that loan provisioning is the most important factor, followed by risk and profitability. Including country risk ratings does not seem to improve their model; however the inclusion of traditional debt ratings as one of the independent variables has a significant positive impact on the model performance. This is an interesting finding as it suggests that BFSRs may not add very much information over and above the traditional debt rating. Although Moody's claims that BFSRs are independent from traditional ratings, it appears that the factors that go into BFSRs are similar to the factors that underlie debt ratings. This finding makes it interesting to investigate the LT bank ratings further.

In another paper Poon and Firth (2005) focus on the role of unsolicited bank ratings. Lately the practice of unsolicited ratings has prompted controversy as these ratings do not appear to be empirically as favourable as solicited ratings. In the literature we can distinguish two groups of papers on this topic. The first group (Poon, 2003a; Poon, 2003b; Poon and Firth, 2005; Van Roy, 2006) finds that unsolicited ratings are lower than solicited ones. In the other group Butler and Rodgers (2003) find that solicited ratings are not higher than unsolicited ratings and they show that soliciting a rating reduces the impact of financial variables on that rating. As an extension to previous research on corporate solicited ratings Poon and Firth (2005) investigate the issue for bank ratings provided by Fitch. As for the corporate unsolicited ratings (Poon 2003a, 2003b), they find that in an international sample of 1060 bank ratings, a significant difference exists between solicited and unsolicited ratings and find that the shadow[41] group has lower ratings, which is partly due to the fact that these banks are typically smaller and have less robust financial health. Furthermore using a two-step treatment model, Poon and Firth (2005) show that bank size, profitability, asset quality, liquidity and sovereign risk are important determinants of Fitch January 2002 bank ratings. Using a sample of Asian banks rated by Fitch, Van Roy (2006) finds similar results and concludes that unsolicited bank ratings tend to be lower than solicited ones even after accounting for differences in observed bank characteristics. Even though it would be very interesting to further investigate this issue, we lack the necessary data. As Moody's does not provide any unsolicited ratings and as our final dataset only included few unsolicited S&P ratings, we have decided to exclude unsolicited ratings from our sample.

[41] Some rating agencies prefer to use the term "shadow" or "pi" for ratings that are unsolicited and hence largely based on public information.

In corporate rating literature there has already been a significant amount of research on split bond ratings. Ederington (1986) finds that differences between bond ratings by Moody's and S&P result from random differences in opinion rather than from differences in rating standards or rating determinants. In later work it is shown by different authors that rating scales and rating determinants do differ across rating agencies when due account is taken of the self-selection bias (e.g. Cantor and Packer, 1997; Pottier and Sommer, 1999). Even though it is shown by Morgan (2002) that there are more split ratings for banks than for corporates, this issue has not been thoroughly addressed for bank ratings. An important consideration when dealing with split ratings is the reason why a bank would opt for a rating from more than one CRA[42]. According to financial intermediation theory, the principal role of external ratings is to reduce information asymmetry about a firm's ex-ante economic value and likelihood of financial distress (Millon and Thakor, 1985). As such, the higher the probability of disagreement between various stakeholders on the bank's insolvency risk, the higher the demand for a rating.

A first proxy for uncertainty is size measured by the logarithm of total assets. The relationship between uncertainty and size is a double-edged sword. Bigger banks are more diversified, but greater size also means that one has to consider whether managers are able to cope with more complex issues and thus uncertainty (Demsetz and Strahan, 1997). The additional lack of transparency for banks is induced by the bank's asset base; banks hold very few fixed assets, which may invite asset substitution and other agency problems between owners, managers and creditors. In addition, financial assets, another typical characteristic of banks, generally create collateral uncertainty. Furthermore the opaque loans held by banks may invite agency problems as well (see Diamond, 1984). The above is all reinforced by banks' high leverage, which creates agency problems and further increases uncertainty over their assets. Shareholders of leveraged firms are inclined to take more risk than creditors bargained for (Jensen and Meckling, 1976). Based on Cantor and Packer (1997), we also include profitability as they argue that relatively high levels of profitability and leverage are positively related to the level of uncertainty. As such, taking into account data availability, we will include the following accounting variables in the selection equation (infra): size measured by ln(assets), leverage measured by debt to equity, type of assets measured by fixed assets/total assets and loans/total assets and profitability measured by cost-to-income. Furthermore we will include a dummy for whether the bank is quoted. A publicly traded bank has outside investors who are also interested in its solvency. Thompson and Vaz (1990) find that since investors value the certification function of CRAs, bond issuers benefit from obtaining more than one rating. In addition, quoted banks have a higher probability of issuing rated debt, which means that the marginal cost of obtaining a bank rating is probably lower when they have already obtained a debt rating from that CRA. For the above reasons

[42] As was mentioned, in our analysis we only include solicited ratings of Moody's and S&P. In this way we assure that it was the bank itself that requested the rating.

we claim that quoted banks have a higher likelihood of obtaining more than one rating. This assumption is supported by our sample.

3.3 Data and methodology

3.3.1 Data

For this research, 4 types of variables are required: the ratings, financial variables, country-specific variables and macro-economic indicators. We will discuss them in turn.

3.3.1.1 Ratings

Credit ratings are applied to issuers and individual debt issues separately. As we are interested in explaining the purest measure of bank default risk, we use the LT bank ratings which are an indication of the ability of banks to honour ongoing financial obligations. The source of our rating data are S&P RatingXpress and Moody's Rating Interactive. As mentioned before, we focus on the period 2000 to 2009 and our sample includes both US and European banks. For the period 2000 to 2009 this initial dataset included 1819 and 4005 different banks rated by Moody's and S&P respectively. By limiting the sample to European and American banks and after matching the rating data with Bankscope data (infra), 2373 different S&P rated banks and 795 different Moody's rated banks were left. Our final dataset will be discussed in more detail in the paragraph on data pre-processing.

Our sample includes banks over the entire ratings spectrum, including both banks at investment and below investment grade. The rating classes, which are given on a scale from AAA to D (S&P) and Aaa to C (Moody's), were transformed into a numerical scale. More specifically we have recoded the rating scales in 7 ratings grades in order to avoid the occurrences of rating categories with few observations (see amongst others Amato and Furfine, 2004). Without loss of generality we assign 1 to AAA/Aaa, 2 to AA/Aa and 7 as of CCC/Caa.

Furthermore, in order to minimize the inclusion of observations that would lead to double-counting, we will use annual rating observations. More specifically and in line with prior studies, we will use December as a reference month (e.g. Amato and Furfine, 2004; Blume et al., 1998).

3.3.1.2 Financial accounting data

One objective of the paper is to develop a model that helps to explain LT bank ratings by using accounting and financial variables of the bank. The rating determinants that are part of our model are based on both industry experience and academic research, and are extracted from the Bankscope dataset. Bankscope is a comprehensive database of bank financial statements that currently contains information on 30 000 banks from all over the world.

Table 3.3 gives an overview of the different financial variables we have used in our analysis. They cover the most important measures of liquidity, profitability, solvency, asset quality and operational efficiency. To avoid multicollinearity problems, we cannot include all variables in one regression and in order to arrive at the best model we try to include at least one parameter of these 5 dimensions.

Besides the traditional financial ratios, we have also included a new [43] accounting data-based measure, the so called Z-index, which represents a more universal measure of bank risk. It is defined as ln(Z) with Z equal to $\left[ROA + EA/\sigma(ROA)\right]$, where ROA is the rate of return on assets, EA the ratio of equity to assets and σ(ROA) an estimate of the standard deviation of the ROA. To calculate the standard deviation of ROA we use data from the three previous years and the five previous years and checked whether it gave similar results (infra). The Z-index is monotonically associated with a bank's distance to default and has been widely used in the empirical banking and finance literature (e.g. Boyd et al., 2009; Laeven and Levine, 2009). A higher Z indicates that a bank is more distant from insolvency. Since Z is highly skewed, we use its natural logarithm, which is normally distributed.

Furthermore, we include a consolidation dummy, an audited statement dummy and a specialisation dummy.

Based on literature, we include 3-year averages of the financial ratios in our analysis. As Moody's and S&P claim that they are rating TTC we will also estimate our models with 5-year averages. Furthermore in order to assure that our financial ratios are accurate measures of credit quality, we will subtract their within-year cross sectional averages. By using these demeaned measures in our analysis, we avoid that our independent variables are picking up cyclical or secular effects.

3.3.1.3 Country variables

The banks in our dataset originate from 38 different countries (see Table 3.4), which makes it very important to account for potential cross-country effects. During the exploration of the data, we included country dummies and region dummies which indeed confirmed the existence of country effects. An important cause of these effects is the difference in regulation and supervision. Some papers have already investigated whether better banking supervision and regulation are associated with sounder banks. Demirguc-Kunt and Detragiache (2008, 2010) investigate this issue by including indirect measures for supervision and regulation such as the quality of bureaucracy for example, and find that there are less banking crises in countries with better institutions. This is in line with Barth et al. (2001, 2008), who show that regulatory approaches that facilitate private sector monitoring of banks (e.g. the disclosure of reliable information) and strengthen incentives for market monitoring (e.g. limited deposit insurance) improve bank performance and stability. In contrast, boosting supervisory oversight and tightening capital standards do not improve banking sector development nor does it reduce banking system fragility. Laeven and Levine (2009) extend this analysis and show that the impact of regulations on bank risk-taking also varies with the comparative power of shareholders within the corporate governance structure of each bank. More specifically they find that depending on the bank's corporate governance structure the same rules and regulations will have a different impact on its risk taking. Furthermore, Cihak and Tieman (2008) find that high-income countries have better regulation and supervision than low-income countries. In these papers, bank soundness is measured by a Z-score, Moody's bank financial strength ratings, a dummy variable for systemic crises etc. Up to this point, the relation between LT bank ratings[44] and supervisory or regulatory practices has not been investigated. The above findings however, suggest that after controlling for financial variables, banks that are located in countries with higher-quality supervision or regulation should receive a better rating. As proxies for supervisory and regulatory quality we will rely on the extensive dataset of Barth et al. (2001, 2006, 2008), who were the first to assemble and analyze an extensive dataset on bank laws and regulations using various studies around the world. Their goal was to build a dataset that would allow "policy makers to draw conclusions on key priorities in making their regulatory and supervisory framework more robust". The initial dataset stems from 2001 and was updated in 2003 and June 2008; we have included all three years in our analysis. For a further description of the variables that we include, we refer to Table 3.5.

Besides the bank regulatory environment we also include the corruption index of Fons (1998), which is an indication of the corruption perception and can be used as a measure for the transparency of a country. Fons (1998) shows that after the Asian financial crisis, there was an urgent need for the revival of interbank confidence which, in turn, required credible transparency, massive restructuring and state-financed recapitalization. Moreover, he argues that accounting transparency is vital to the health of a banking system and therefore uses a corruption index as a measure for transparency, motivated by a strong relationship between corruption within a country and the transparency of its bank accounting standards. Countries perceived as being less corrupt on average have stronger banks. He also supports the hypothesis that increased transparency will yield lower overall credit risk and uncovers a correlation between credit risk and a quantitative measure of corruption. We expect a negative sign as a higher corruption perception index indicates that a country is less corrupt and thus should result in a better rating.

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[43] To the best of our knowledge, these measures are new, in the sense that they are used in literature outside the bank rating discipline but this is the first time that they have been used in this context.
[44] From the results of Poon (1999) we can conclude that Bank Financial Strength Ratings are quite different from LT bank ratings (supra).

Furthermore as country dimensions exceed corruption and regulatory practices, we also include a sovereign rating. In line with other credit ratings, sovereign ratings are assessments of the relative likelihood that a government will default on its obligations. These ratings will allow governments to ease their access to international capital markets, where rated securities are preferred over unrated securities of apparently similar credit risk (Cantor and Packer, 1995). We feel it is important to include this variable in our analysis as these ratings affect the ratings of a large number of other borrowers within the same country. The CRAs generally do not assign ratings to issuers that exceed their home country's sovereign rating; and as such sovereign ratings could have an impact on bank ratings as well[45]. In our regressions, we will alternate between Moody's and S&P foreign and domestic currency ratings. As both in the past (e.g. Mexican crisis, 1994) and in the current crisis, it was clear that Moody's and Standard and Poor's frequently disagree on specific sovereign ratings assignments, hence we feel it would be wrong to include sovereign data of only one CRA (Cantor and Packer, 1995).

As the countries in our sample have economies and banking systems of vastly different size, the sample is very unbalanced with some countries represented by only a handful of banks and others with hundreds. The latter is especially true for Germany. To ensure that regression results are not overly influenced by German banks we examine results with and without the German banks.

3.3.1.4 Trend and cycle

The financial system in which banks operate is procyclical, implying that financial activity tends to increase more during booms than during economic downturns. This can be explained by the accelerator model (Bernanke et al., 1999) and the fact that market participants behave as if risk is countercyclical. However, bank credit ratings are not supposed to be procyclical. External credit ratings have been initiated for the benefit of investors who are often less concerned about short run credit events as long as they do not hurt the likelihood of full repayment at maturity. To address this need, rating agencies have applied a through-the-cycle approach where ratings are supposed to be insensitive to short term changes in economic conditions. The longevity of rating agencies suggests that such risk measures have been highly valued by investors. In line with Amato and Furfine (2004) we assume that this TTC implies that a bank's rating should be independent of the state of the business cycle, conditional on the bank's financial and business characteristics. To check for procyclicality we will empirically test whether the macro-economic environment is an important determinant of bank credit ratings after properly accounting for bank-specific factors. We will use different measures for

[45] For example, on 27th April in 2010 every newspaper highlighted that Standard & Poor's had cut Greek bank ratings after a sovereign downgrade. Since Standard & Poor's lowered the sovereign rating of Greece to a BB+ rating (Evans, 2010) and since a bank of a country never can have a better rating than the sovereign rating, Standard & Poor's was obliged to lower the ratings of four Greek banks as well.

cyclicality. First we will check for cyclicality using the recession index. For the US, this index is based on the data of peaks and troughs from the NBER, for Europe, we rely on the business cycle data of the CEPR. Due to the virulent nature of a recession it is plausible to assume that it has a stronger impact than an expansion. As such, to ensure that the recession index that we construct, accounts for the asymmetry between both periods of a cycle, it is set to -1 in times of recessions and to 0 during a boom[46]. Hence, this paper will examine whether bank risk ratings are asymmetrically assigned or biased over business cycles from 2000 to 2009. If credit rating agencies are more aggressive with downgrades during recessions and upgrades during booms, this procyclicality will have an impact on bank capital levels, lending activity and the global economy as a whole. Next we will run our analysis with the slope of the yield curve, a commonly used business cycle indicator (e.g. Bernard and Gerlach, 1998). The slope of the yield curve is calculated as the difference between the ten-year government bond yields and the short term rate. We will further run our analysis with inflation[47] and employment growth, two continuous indicators of the state of the economy. The question is then what causes this cyclicality: deterioration in credit quality (e.g. Allen and Saunders, 2003) or the strictness of rating agencies.

In literature we find evidence that suggests that corporate bond ratings by private agencies are influenced by business cycle conditions. Altman and Kao (1992) find that Moody's and S&P ratings are autocorrelated. This implies that rating downgrades are more likely to be followed by downgrades than by upgrades, implying that rating assignments might not be independent. Further Amato and Furfine (2004) find that initial and newly assigned S&P ratings are related to the macro-economy in a procyclical manner. After accounting for specific measures of company risk they find that ratings are worse during recessions and better during a boom. In doing this analysis, we should keep in mind that some co-movement with business cycle measures cannot be excluded since we are never able to fully capture the business and financial risk banks are exposed to (see Löffler, 2004). This omitted variable issue can never be completely remedied. However, on the basis of Amato and Furfine's paper we will try to address the issue by performing a weak and strong test of procyclicality. In addition to bank-specific risk factors and in case the business cycle determinant shows to be significant, the strong test will include systematic time variation in risk factors by including cross-sectional averages of the variable in the model as well. However, where Amato and Furfine (2004) have a sample that is dominated by non-financial firms and only relies on S&P data, we focus on banks and include both Moody's and S&P data. Amato and Furfine (2004) explicitly state that results do not necessarily hold for other CRAs, which makes it very interesting to investigate potential differences on this matter

[46] In doing so, we basically assume that only recessions have a material impact on the rating process.
[47] Inflation is measured by the GDP deflator, which is the ratio of GDP in current local currency to GDP in constant local currency and it shows the rate of price change in the economy as a whole. It has the advantage over the consumer price index that it is not based on a fixed basket of goods and services and as such that changes in consumption patterns and the introduction of new goods are automatically reflected in the deflator.

between S&P and Moody's (see Cantor and Man, 2003b). In the current macro-economical environment where supervisors are confronted with major challenges with respect to bank monitoring, it is highly relevant to investigate this issue[48].

Beside the potential procyclicality some authors also argue that credit ratings have deteriorated over time. For instance Lucas and Lonski (1992) found that over a specific timeframe, firms that received a downgrade from Moody's consistently exceed the number of firms that received upgrades. Also Blume et al. (1998) find that CRAs have become stricter over time. Conversely Amato and Furfine (2004) argue that when due account is taken of systematic changes in risk measures, no evidence for this more stringent rating behaviour can be found, and in some cases they even find the reverse. These different conclusions might be induced by differences in rating agencies which will be partly addressed by using data from two rating agencies. To check for this we have specified a linear trend variable which counts from 1 to 10 for the number of years in the data. When this trend variable is positive and statistically significant at high levels, this would indicate that rating agencies have generally become stricter over time.

Except for the paper by Curry et al. (2008), which investigates procyclicality for non-public BOPEC ratings, we are not aware of any related research on bank ratings. In their paper Curry et al. (2008) only consider newly assigned risk ratings by estimating models with mostly 1-quarter lags prior to the inspection.

3.3.2 Data pre-processing[49]

As a next step we start pre-processing our data. Banks are eliminated when at least one third of the calculated variables are missing. Next, several ratios have missing values and outliers which could disturb the regression output. These issues are encountered using the methodology described in Van Gestel et al. (2006). To deal with this, we start by replacing missing values with the median variable value of the bank. In case this was not possible the variable is imputed, based on the median sample value and after correction for the relative asset size of the respective bank in the respective year. The outlier issue is addressed taking into account the fact that most independent variables are ratios and as such it could be expected that the distributions of these variables have fat tails with large positive and negative values. In order to prevent these outliers from having a negative impact on the model performance, the most extreme points are selected and reduced to the 3σ-borders in a robust way[50]. For

[48] Syron (1991) claims that supervisors are historically more vigilant during recessions. Furthermore Peek and Rosengreen (1995) conclude that the inability to raise external capital due to regulatory practices resulted in a high number of banks shrinking their assets with possible adverse effects on the banks' lending behaviour.
[49] The most important descriptives of our data are depicted in table 3.7 and 3.8.
[50] This method is basically a kind of winsorising procedure.

the limits m ± 3×s, with m = median, s = IQR(x)/ (2×0.6745) and IQR the interquartile range (Van Gestel et al., 2006) is selected[51]. This is done on an annual basis.

Furthermore, we check whether certain bank variable values are realistic when matched with bank ratings and vice versa. For example, we check whether banks that have negative equity have commensurate ratings. The distributions of the different variables are also analysed. If the distribution of a variable deviates considerably from a normal distribution, a logarithmic transformation ($x \rightarrow \log(1 + x)$) is used to see whether this leads to a significant improvement of the final result.

After pre-processing the data, 2046 different S&P rated banks and 680 Moody's rated banks are left. This final sample reflects the ratings of 1659 different banks that are rated only by S&P, 293 banks rated only by Moody's and 387 rated by both Moody's and S&P. Our sample includes 10 451 S&P bank rating observations obtained from S&P RatingsXpress and 4 290 Moody's bank rating observations obtained from Moody's rating Interactive over the period from 2000 to 2009. We refer to Table 3.8 and 3.9 for an overview of the number of ratings per year and the relative coverage of the population of bank ratings. In Table 3.9 we also provide an overview of the number of banks that are rated by both Moody's and S&P.

3.3.3 Methodology

Our empirical work consists of two sets of models, a first set to determine rating determinants for our full sample and another to analyse the bank ratings of banks that receive both a rating from Moody's and S&P.

3.3.3.1 Ordered logit model for rating determinants

As the dependent variable in our model is an ordinal variable, an ordinal regression should be used (Allison, 1999). More specifically we will use the logit function, which is based on the logistic density function, to link the dependent variable with the independent variable. Logit functions are very useful as their values are restricted to the interval between 0 and 1 and as such may be interpreted as probabilities.

The general ordered logit model is based on the following specification:

$$y^* = \beta x_i + \varepsilon_i$$

The mathematical basis of the ordinal logistic regression is the following equation, which gives the cumulative probability of a rating i:

[51] For the analysis involving split bank ratings, we have re-estimated the outliers based on the new sample of banks.

$$P(y \le i) = \frac{1}{1+\exp(-\theta_i + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n)}, \text{ i=1,…,m}$$

with explanatory variables $x_1, x_2, ..., x_n$, the corresponding coefficients $\beta_1, \beta_2, ..., \beta_n$ and θ_i[52] a parameter linked to a category or in this case a rating i. The latent variable z gives a score for each bank based on the independent variables and the coefficients (Van Gestel et al., 2006).

$$z = -\beta_1 x_1 - \beta_2 x_2 ... - \beta_n x_n$$

The score of a bank can be used to determine the score of a bank per rating.

$$z_i = \theta_i - \beta_1 x_1 - \beta_2 x_2 ... - \beta_n x_n$$

or: $z_i = \log\left(\frac{P(y \le i)}{1 - P(y \le i)}\right)$

The score of a bank per rating can be used to calculate the cumulative probability of a certain rating and the probability of a rating.

$$P(y \le i) = \frac{1}{1 + e^{-z_i}}$$

$$P(y = i) = P(y \le i) - P(y \le i - 1)$$

In performing a regression, STATA will estimate the parameters $\theta_{1,...,}\theta_m$ and $\beta_{1,...}\beta_n$ using a maximum likelihood procedure that minimizes the negative log likelihood (NLL) (Van Gestel et al., 2006):

$$-\sum_{i=1}^{m} \log(P(y = i))$$

We ran our analysis using December as a reference month[53]. In order to detect whether the rating agencies have changed their model under the pressure of the recent financial turmoil we have analyzed our data both in a cross-sectional and in a panel data setting. More specifically we will report the results for the year 2009 and for the period 2000-2009.

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[52] As $P(y \le m) = 1$, the parameter θ_m is equal to ∞.

[53] As a robustness check we have run the analysis for the month of April as well. However as there are no significant differences, we will only report December.

3.3.3.2 Multilevel logistic regression

In order to account for within country dependency, the cross sectional standard errors are clustered by country. In doing so, we allow correlated residuals within each country. In the panel data analyses we will account for the dependency within banks across time and across countries.

We have first run a single level ordinal logistic regression, in which we accounted for the clustered nature of the data, in order to obtain Huber White standard errors[54]. However, this model unrealistically assumes that the responses on the same bank are conditionally independent given the covariates. In order to account for the longitudinal dependence/intraclass correlation we have included a bank specific random intercept. This model can be written in terms of a latent response formula as follows:

$y^*_{ij} = \beta_2 x_{2ij} + \beta_3 x_{3j} + ... + \zeta_{1j} + \varepsilon_{ij}$ where $\varepsilon_{ij} \mid x_{ij}$, ζ_{1j} are independent across banks and observations.

To allow the slope of the time variable to vary randomly between banks, we also ran a random coefficient model. However, the likelihood ratio test rejected the random coefficient model in favour of the random intercept model. In a next step we ran a three level multinomial logistic random intercept model for observations *i* nested in banks *j* who in turn belong to countries *k*.

3.3.3.3 Variable selection

To guard against overfitting of data, we randomly divide our sample into two main sub-samples: the estimation sample (70%) and the hold-out sample (30%). The in-sample is used to estimate our model; more specifically we use these observations to see what variables have a significant impact on the S&P and Moody's bank ratings and to estimate the corresponding coefficients. The model validation is done on the hold-out sample.

In order to arrive at the best model, we apply several methods to select the significant variables. We first do a stepwise regression, which basically combines backward and forward regression in one. Variables that are eliminated in a prior phase (due to high p-value) can be added to the model later on if they prove to be significant. However as this is a heuristical procedure, we decide to run several regressions manually with alternating input variables. Due to multicollinearity[55] among the independent variables a lot of them can only be included in the regressions one at a time. A correlation matrix and the variance inflation factors guided us throughout the selection of variables. We include variables that cover the different areas, namely liquidity (e.g. liquid assets/total assets), solvency (e.g.

[54] The correction of the standard errors to account for the intraclass correlation is a weaker form of correction than using a multilevel model. The latter does not only account for the intraclass correlation, but also corrects the denominator degrees of freedom for the number of clusters. When you use clustered robust standard errors, the denominator degrees of freedom are based on the number of observations, not on the number of clusters.

equity/debt), profitability (e.g. ROA), asset quality (e.g. loan loss provisions/loans) and operational efficiency (e.g. overhead/total assets). In our baseline regression we also include country-related variables. We then check what variables are significant at several levels and whether the coefficient of the variables has the right sign, implying that the sign corresponds to the expected sign from an intuitive economic point of view. Wrong signs can be due to bad data quality, spurious correlation or limited data. If a coefficient has a wrong sign, the variable is eliminated from the initial regression. Next, we investigate the role of the business cycle/recession and the trend variable.

3.3.3.4 Two-step ordered-logit model for rating differences accounting for selectivity bias

It is sometimes argued that Moody's and S&P mimic each others' behaviour when rating banks that are rated by both rating agencies. In our sample the Spearman rank correlation between Moody's and S&P ratings amounts to over 85%. However, correlations only measure the relative agreement between CRAs and might not capture differences in average ratings. For instance the kappa statistic[56] in our sample only amounts to 0.16 for banks rated by Moody's and S&P. This is in line with the findings of Morgan (2002) who shows that the level of disagreement across CRAs is much higher for financial intermediaries than for ordinary corporates. Explanations for differences (see Table 3.10 and 3.11) across agencies are scarce. Ederington (1986) has proposed 3 sources for divergence in rating opinions across CRAs: different cut-off points, different determinants or different weighing of determinants and random variation in judgement. As such we would like to test our findings on the sample of bank ratings that are rated by both rating agencies. As descriptive statistics revealed that there are quite some differences between banks that are rated by only one CRA and those that are rated by both, we should account for potential sample-selection bias. We will address this issue for banks that receive a rating from both Moody's and S&P in 2009. More specifically we will run a model that consists of two stages and controls for sample selection bias. The latter is a concern whenever the response variable is observed only if a selection condition is met. Problems arise because standard regression techniques result in biased and inconsistent estimators if unobserved factors affecting the response are correlated with unobserved factors affecting the selection process (Heckman 1978, 1979). More specifically, the first stage is a probit regression modelling the decision to obtain both Moody's and S&P rating and the second stage is an ordered logit regression modelling the rating determinants. As we want to study the differences between both rating agencies after account is taken of this selectivity bias and to avoid inconsistent parameter estimates, a two-step ordered logit model will be used. If sample selection were random, the expected error term conditional on obtaining both ratings

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[55] The primary concern of multicollinearity is that the regression model estimates of the coefficients could become unstable and the standard errors for the coefficients could get wildly inflated.

[56] The kappa statistic is a measure of disagreement that originates from biometrics and was used by Morgan (2002) to measure disagreement between raters. Kappa= $[p_o - p_e]/[100 - p_e]$ where p_o is % of equally rated banks observed and p_e is % of equally rated banks that one would expect, taking into account the distributions of the rating. As such, Kappa locates CRA along the spectrum of complete disagreement (kappa=0) and complete agreement (kappa=1).

would be zero. However if sample selection is non-random and there are systematic reasons why banks would choose to be rated by both rating agencies, the expected error term conditional on a bank obtaining both ratings would not be zero (see e.g. Heckman, 1979; Cantor and Packer, 1997; Poon (2003)). This could be motivated by the fact that a bank knows that taking into account its degree of uncertainty, an additional rating is required to reduce its opacity to an acceptable level (supra). The standard selection model developed by Heckman has been extended to ordinal random variables by Greene (1995).

Basically in addition to obtaining estimated coefficients, the correlation ($\rho_{\xi\varepsilon}$) between the error term from the decision to obtain two ratings (ξ_i) and the error term from the rating model itself (ε_i) are also obtained. More specifically we will test whether $\rho_{\xi\varepsilon} = 0$ (Greene, 1997). The probit model for sample selection is given by $S* = \alpha Z_i + \xi_i$ where the observed decision is $S_i = 1$ if $S_i^* = 1 > 0$ and $S_i^* = 1 \leq 0$. With S_i being the binary variable indicating whether a bank has two ratings, S_i^* a continuous unobserved variable measuring the propensity to obtain two ratings and Z_i the vector of explanatory variables[57].

[57] With a higher and positive value for α as an indication of a higher probability to obtain two ratings.

3.4 Results

The results of S&P and Moody's will be discussed in turn. As mentioned we have run several analyses and we will report the models with the highest out-of-sample performance[58].

3.4.1 S&P rating determinants applying a Random Intercept Model

3.4.1.1 S&P 2000-2009

This first section discusses the estimation results of the ordered logit model based on our baseline regression including financial and country related variables. For the complete S&P dataset including the observations from 2000 to 2009, we obtain the following significant parameters for the ratings of December[59]: the demeaned 3 year averages of lnassets (-)***, Cost/Income (+)***, LLP/Loans(+)**, Liquidassets/Deposits and borrowing (-)***, Eq/TA(-)***, Lnzindex3y** (-), S&Psrforeign(+)***(see Table 3.14)[60]. So the Z-index, a variable that has not yet been investigated in relation to bank ratings, seems an important determinant of LT S&P bank ratings[61]. Obviously banks that have a higher distance to default will receive a more favourable rating. The other variables confirm the dimensions that Poon et al. (2005) found to be significant for Fitch bank ratings. First, size seems to be a very important determinant and as expected it contributes positively to the bank rating. Bigger banks are assumed to be more diversified and will be better able to survive shocks. The latter could also be interpreted as the "too big to fail" assumption of many investors, where they expect a government bailout of systemic important financial institutions when they get into trouble. Further, in line with our expectations, higher liquidity, profitability, solvency and asset quality will result in a lower, thus better rating. More specifically a high cost-to-income ratio and high loan loss provisions will result in a higher thus worse rating, whereas high liquid assets relative to deposits and borrowing and high equity relative to assets will result in a lower thus better rating.

Insert Table 3.14 here

With respect to country specific variables, the sovereign rating seems to be very important. The S&P model had a higher performance with the S&P foreign sovereign rating than with the Moody's foreign sovereign rating, for the Moody's model (infra) the reverse was true. Furthermore, excluding the country specific variable, results in a model with significant lower out-of-sample performance.

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[58] Alternative models with different combinations of variables have been tested. However, taking into account that the variables should have the intuitive correct sign, the reported models achieves the best match.
[59] ***, ** and * indicate significance at the 1% 5% and 10% level.
[60] The correlation matrix of the variables included in our analysis is depicted in Table 13.
[61] However, compared to Poon et al. (2005), our best model includes slightly different variables to measure bank profitability, asset quality, solvency and liquidity.

Due to multicollinearity we cannot include both the sovereign index and the corruption index in our analyses. However, if we include the corruption index, it is also a significant determinant of S&P ratings with the expected (negative) sign[62].

The estimated coefficients all have the correct estimated and economically significant sign. In logit models, there is no natural magnitude for the linking variable, so we should be careful when interpreting the economic significance of the coefficients as such. However, what can be deducted from Table 3.14 is that the likelihood ratio test rejects the hypothesis that all parameter coefficients are zero.

The out-of-sample model performance is measured by notch difference graphs. A notch difference graph is a histogram showing cumulative accuracy for increasing notch differences between the S&P rating and the rating estimated by the model. The notch difference graph depicted in Figure 3.1 indicates that our model performs very well out-of-sample, with 68% of the ratings estimated correctly and almost 95% of the ratings estimated correctly up to one notch.

Insert Figure 3.1 here

In a next step we have included a linear trend and a business cycle indicator. As is shown in Table 3.15 the trend variable has a negative sign - which might imply[63] that S&P has become less stringent over time in rating banks – but is insignificant. So, the bank ratings of S&P show no trend behaviour, indicating that S&P neither became more lenient nor stricter in the course of the past decade. This finding could be partly influenced by the staleness inherent in ratings. Due to the fact that monitoring is costly and time consuming, it is unlikely that a rating agency can devote sufficient time and resources to examine all rated firms on a continuous basis.
Furthermore also the recession index, the slope of the yield curve, employment growth and inflation are found to be insignificant. So, none of the business cycle indicators seems to be a significant determinant of LT S&P bank rating. As such, our model indicates that S&P bank ratings are indeed through the cycle as they are not significantly influenced by the economic conditions. As was mentioned before, in order to understand the extent and source of cyclicality, we could also conduct a "strong" test, where we include the time series of the yearly cross-sectional averages of all financial variables, including both a trend and cyclical component. Including these may provide further

[62] Including the corruption index instead of the sovereign ratings, results in a model with lower model performance.

information on whether systematic time variation in the accounting variables can explain any finding of a significant secular or cyclical influence on ratings (see Amato & Furfine, 2004). However as our analyses show that the cycle indicators do not seem to be significant, we can skip this step.

Insert Table 3.15 here

We have also run our analysis with 5-year averages. We get qualitatively similar results with a slightly higher out-of-sample performance (see Table 3.14 and Figure 3.2). This finding further supports the notion that S&P is rating quite stable throughout the cycle.

Insert Table 3.14 here

Insert Figure 3.2 here

3.4.1.2 S&P 2009

When we estimate the cross-sectional model for the ratings of January 2009, all the same variables are significant, which is again a finding in favour of the TTC philosophy S&P applies (see Table 3.19 and Figure 3.7 and 3.8). This basically could indicate that S&P did not change its rating model during the recent turmoil.

Insert Table 3.19 here

Insert Figure 3.7 and 3.8 here

3.4.2 Moody's rating determinants applying a Random Intercept Model

3.4.2.1 Moody's 2000-2009

For the complete Moody's dataset including the observations from 2000 to 2009, we obtain the following significant parameters for the ratings of December: the demeaned 3-year averages of lnassets(-)***, Operatingexp/TA (+)***, Liquidassets/TA*** (-), Eq/Liab(-)***, Cost/Income(+)***, LLP/Loans(+)***, and the Moody's srforeign***(+). So, as was the case with S&P, the traditional dimensions that were identified a priori are being confirmed. The estimated coefficients all have the

[63] As the assessment of credit risk is subjective by nature, it is plausible that our models fail to account for certain variables, as the assessment of creditworthiness. Due to this omitted variable bias, we cannot claim to have found that there is a drift or that S&P ratings are not excessively procyclical. We can only say that our results indicate that this might be the case.

correct estimated and economic significant sign (see Table 3.16). The notch difference graph is depicted in Figure 3.4. As is shown almost 50% of the ratings are estimated correctly and 95% of the ratings are estimated correctly up to one notch.

Insert Table 3.16 here

Insert Figure 3.4 here

As for the S&P ratings, including the corruption index results in a comparable model with the corruption index having a significant negative sign, but lower model performance. In a next step, to convince us of the fact that Moody's is indeed using a different model than S&P, we run the S&P model on the Moody's rating data. However as this resulted in a much lower out-of-sample model performance – a zero notch difference of only 35% - we will not further elaborate on this[64,65].

In a subsequent step we have included a linear trend and our business cycle indicators. As is shown in Table 3.17, the linear trend is significant and has a negative sign. This could imply that Moody's, has become less stringent over the period 2000 to 2009. Furthermore the recession index is insignificant, which could indicate that Moody's does not become more severe in times of recession. However, the other business cycle indicators – the slope of the yield curve, inflation and employment growth - are significant, suggestive for cyclicality.

Insert Table 3.17 here

As such in a next step we have included yearly means of the financial variables in order to account for systemic time variation in the risk factors. After due account is taken of systematic time variation in financial variables, there is evidence of excessive cyclicality when the slope of the yield curve and employment growth are used as a business cycle indicator (see Table 3.18). The time drift disappears in all cases. So, our findings of a secular relaxing of ratings standards are not robust to a more complete accounting of systematic changes to measures of risk.

Insert Table 3.18 here

[64] This lower out-of-sample performance is due to the fact that certain variables that are significant for S&P (e.g. the Z-index) are not significant for Moody's and vice versa (e.g. operatingexp/ta).

[65] We also run the best model for Moody's on S&P rating data. However this also resulted in inferior out of sample performance with less than 50% of the bank ratings estimated correctly and about 10% of the bank ratings that are estimated wrong with 2 notches or more.

3.4.2.2 Moody's 2009

The possibility of excess cyclicality is further supported after estimating the cross-sectional model. Where S&P basically used the same model in 2009 than before, it seems that the model for Moody's has changed. More specifically the next variables are now significant: 3-year averages of Eq/Liab (-)**, lnassets(-)***, Operatexp/TA(+)***, Liqass/TA(-)* and the Diversificationandliquidityindex ***(-) (see Table 3.19). So, cost-to-income, LLPtoloans and the Moody's srforeign are no longer significant and the diversificantion and liquidity index is now included in the model. Furthermore, including 5-year averages, results in a different model with different out-of-sample performance (see Figure 3.9 and 3.10).

Insert Table 3.19 here

Insert Figure 3.9 and 3.10 here

What is also apparent is that it is much more difficult to forecast Moody's ratings using the information we have in our dataset. This could imply that Moody's is using more qualitative data or that there is more discretion in their ratings. Ratings are a result of combining objective statistical models (rules) and subjective judgments (discretion). They are influenced by different elements where experience and expert judgment keep playing an essential role.

In order to ensure that our results are not over influenced by the overrepresentation of Germany in our sample, we ran our analysis without that country and find overall similar results both for Moody's and S&P.

3.4.3 Rating Determinants applying Sample Selection Model

As is shown in Table 3.20, for S&P rated banks, size, the cost-to-income ratio, stock listing and type of assets seem to have a significant impact on the decision to be rated by both rating agencies. Our findings support the idea that as bigger banks are coping with more complex issues and uncertainty, they will benefit from an additional rating (Demsetz and Strahan, 1997). They further confirm that quoted banks believe that their outside investors value the certification function of CRAs and/or that their marginal cost of obtaining a bank rating on top of a public debt rating is lower. In line with Cantor and Packer (1997), we also find that more profitable banks have a higher tendency to obtain a second rating. Furthermore the asset base of banks, and more specifically the opaque loans, further reduces the bank's transparency and increases the incentive to ask for an additional rating.

Insert Table 3.20 here

The likelihood-ratio test rejects the null hypothesis of rho[66] - the correlation between errors in selection and outcome equation - equal to zero at a significance level of 1%, implying that sample selection is present. After controlling for nonrandom selection, all variables stay significant with the correct estimated sign. This finding indicates that S&P uses the same model for banks that are also rated by Moody's.

For banks rated by Moody's, the decision to obtain an additional rating from S&P seems to be random. The likelihood-ratio test can not reject the null hypothesis of rho - the correlation between errors in selection and outcome equation - equal to zero. This basically would suggest that data are missing randomly or that the regression coefficients of the selection model and the regression coefficients of the rating determinants model were estimated by unrelated processes[67]. When we control for nonrandom selection, most variables remain significant with the correct sign. However as there is less evidence of selection bias, we can estimate our single equation. This results in a model where all variables have the correct estimated sign, but the liquidity measure and the solvency measure are no longer significant.

These findings could indicate that Moody's perhaps slightly adjusts its model when rating banks that are rated by S&P as well.

3.5 Conclusion

This paper presents a joint examination of how different factors influence the assignment of S&P and Moody's long term bank ratings using a unique data set covering different regions, bank sizes, and bank types. In doing so, we include new and accurate measures of bank and country specific variables. We find that S&P and Moody's use a different rating process. More specifically when we analyse S&P bank ratings we find the same variables to be significant in a panel data setting from 2000 to 2009 and in the year 2009. This could indicate that S&P is rating through-the-cycle, which is further confirmed by the fact that no business cycle indicator seems to have a significant impact on the S&P bank ratings.

[66] I will not further interpret rho as there as it is extremely sensitive to model specification. Alternative model specifications will change the errors, which in turn will change rho. Furthermore I presume that whatever is the cause of the correlation between u and e should be inherently immeasurable (see Stolzenberg, 1997).

[67] A robust selection equation is one of the most important things in selection modelling. As for Moody's only 2 variables are significant in the selection model, we should be careful when interpreting the results.

Moody’s seems to adjust its rating process throughout time. Different indicators are significant for the period 2000 to 2009 compared to the period 2009. Furthermore we find that 3 out of 4 business cycle indicators are significant. After controlling for cyclical changes to business and financial risks, the slope of the yield curve and employment growth stay significant as a cycle indicator. Both of these findings could be interpreted as an indication of excess cyclicality even when it is only to a small extent.

Even though our focus is on the cyclical properties of ratings, we also provide evidence on trend behaviour of bank ratings. In particular, our results indicate that previous findings of a secular tightening of corporate rating standards do not hold for banks. Both for Moody’s and S&P, we actually find that after the inclusion of more complete measures of systematic changes to risk, no significant trend behaviour exists.
Finally, we checked our findings on a sample of banks that are rated by both ratings agencies while controlling for potential sample selection bias. We find only limited evidence of mimicking behaviour between Moody’s and S&P.

Our findings are highly relevant for various bank stakeholders, who often tend to assume that Moody’s and S&P have equivalent rating scales and rating processes. This paper shows clear evidence that this is not the case. Moody’s and S&P have different rating determinants, different sensitivity towards the business cycle and behave differently when rating banks that are rated by both of them.

3.6 References

Allen L., Saunders A., 2003. A survey of cyclical effects of credit risk measurement models, BIS Working Paper no. 126.

Allison P., 1999. Logistic regression using SAS: theory and Application. SAS Press.

Altman E., Katz S., 1976. Statistical bond rating classifications using financial and accounting data. In Michael Schiff and George Sorter (eds.), Proceedings of the Conference on Topical Research in Accounting. New York: New York University Schools of Business.

Altman E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance 23, 589-609.

Altman E.I., 1989. Measuring corporate bond mortality and performance. Journal of Finance 44, 909-922.

Altman E. I., Kao D.L., 1992. The implications of corporate bond ratings drift. Financial Analysts Journal, 64-75.

Altman, E., Bharath, S., Saunders, A. 2002. Credit ratings and the BIS capital adequacy reform agenda. Journal of Banking & Finance 26, 929-951.

Altman E., Saunders A., 2001. An analysis and critique of the BIS proposal on capital adequacy and ratings. Journal of Banking & Finance 25, 25-46.

Altman, E., Wilson, N., Sabato, G., 2009. The value of qualitative information in SME risk assessment. NY Stern Working Paper.

Amato J., Furfine C.H., 2004. Are credit ratings procyclical? Journal of Banking & Finance 28, 2641-2677.

Ang J.S., Patel K.A., 1975. Bond rating methods: comparison and validation. Journal of Finance 30, 631-640.

Baker, H.K., Mansi, S.A., 2002. Assessing credit rating agencies by bond issuers and institutional investors. Journal of Business Finance and Accounting 29, 1367-1398.

Barth J., Caprio G., Levine R., 2001. The regulation and supervision of banks around the world: a new database. University of Minnesota Financial Studies Working Paper No. 0006; World Bank Policy Research Working Paper No. 2588, 92.

Barth J., Caprio G., Levine R., 2006. Rethinking bank regulation: till angels govern. Cambridge University Press, New York.

Barth J.R., Caprio G.J., Levine R., 2008. The regulation and supervision of banks around the world: a new database. Working paper.

Beck T., Demirguc-Kunt A., Levine R., 2006. Bank concentration, competition and crises: first results. Journal of Banking and Finance 30, 1581-1603.

Bernard H., Gerlach S., 1998. Does the term structure predict recessions? The International Evidence. International Journal of Finance & Economics 3, 195-215.

Beynon, M.J., 2005. Optimizing object classification under ambiguity/ignorance: application to the credit rating problem. Intelligent systems in Accounting, Finance and Management 13, 113-130.

Bernanke B.S., Gertler M., Gilchrist S., 1999. The financial accelerator in a quantitative business cycle framework. In Handbook of Macroeconomics, Volume 1C, Handbooks in Economics, vol. 15. Amsterdam: Elsevier, 1341-93.

Blume M.E., Lim F., MacKinlay A.C., 1998. The declining credit quality of US corporate debt: Myth or reality? Journal of Finance 53, 1389-1413.

Brister, B.M., Kennedy K.E., Liu P., 1994. The regulation effect of credit ratings on bond interest yield: the case of junk bonds. Journal of Business Finance and Accounting 21, 511-531.

Brockett P., Golden L., Jang J., Yang C., 2006. A comparison of neural network, statistical methods, and variable choice for life insurers' financial distress prediction. Journal of Risk and Insurance 73, 397-419.

Butler A.W., Rodgers K.J., 2003. Relationship rating: how do bond rating agencies process information? Unpublished working paper, Pennsylvania State University.

Cantor R., Packer F., 1995. Sovereign credit ratings. Current issues in Economics and Finance 1, 1-6.

Cantor R., Packer F., 1997. Differences of opinion and selection bias in the credit rating industry. Journal of Banking & Finance 21, 1395-1417.

Cantor R., Mann C., 2003a. Measuring the performance of corporate bond ratings. Moody's Special Comment, April.

Cantor R., Mann C., 2003b. Are corporate bond ratings procyclical? Moody's Special Comment, October.

Carey M., Hrycay M. 2001. Parameterizing credit risk models with rating data. Journal of Banking & Finance 25, 195-270.

Chava S., Jarrow, R. 2004. Bankruptcy prediction with industry effects. Review of Finance 8, 537-569.

Coats K.P., Fant L.F., 1993. Recognising financial distress patterns using neural network tool. Financial Management 22, 142-155.

Chaveesuk R., Srivaree-Ratana C., Smith A.E., 1999. Alternative neural networks approaches to corporate bond rating. Journal of engineering-valuation and cost analysis 2, 117-131.

Cihak, M., Tieman, A., 2008. Quality of financial sector regulation and supervision around the world. IMF Working Paper 08/190. International Monetary Fund, Washington.

Crouhy, M. Galai, D., Mark, R., 2001. Parametrizing credit risk models with rating data. Journal of Banking & Finance 25, 47-95.

Curry T.J., Fissel G.S., Hanweck G.A., 2008. Is there a cyclical bias in bank holding company ratings. Journal of Banking & Finance 32, 1297-1309.

Daubie M., Levecq Ph., Meskens N., 2002. A comparison of the rough sets and recursive partitioning induction approach: an application to commercial loans. International Transactions in Operational research 9, 681-694.

De Larosiere J., 2009. The High-Level Group on Financial Supervision in the EU, Report, Brussels, 25 February.

Demirgüç-Kunt A., Detragiache E., Tressel T., 2008. Banking on the principles: compliance with Basel Core Principles and bank soundness. Journal of Financial Intermediation 17, 511-542.

Demirgüç-Kunt A., Detragiache E., 2010. Basel Core Principles and Bank Risk: dies compliance matter? IMF Working Paper WP/10/81.

Demsetz, Rebecca S., Strahan P.E.. 1997. Diversification, size, and risk at U.S. bank holding companies. Journal of Money, Credit, and Banking 29, 300-313.

Diamond D.W., 1984, Financial intermediation and delegated monitoring. Review of Economic Studies 51, 393-414.

Dutta S., Shekhar S., 1988. Bond rating: a non-conservative application of neural networks. IEEE International Conference on Neural Networks 2, San Diego.

Ederington, L.H., 1986. Why Split Ratings Occur. Financial Management 15, 37-47.

Ederington, L., Yawitz J., Roberts B., 1987. The informational content of bond ratings. Journal of Financial Research 10, 211-226.

Estrella A., Mishkin F.S., 1997. Is there a role for monetary aggregates in the conduct of monetary policy? Journal of Monetary Economics 40, 279-304.

Estrella, A., Park, S., Peristiani, S., 1999. Capital ratios and credit ratings as predictors of bank failures. WP, Federal Reserve Bank of NY.

Florez-Lopez R., 2007. Modelling of insurers' rating determinants. An application of machine learning techniques and statistical models. European Journal of Operational Research 183, 1488-1512.

Fons J.S., 1998. Asia: an analysis of financial crisis. Moody's Investor Service Paper.

Gentry J.A., David T., Newbold P., 1988. Predicting industrial bond ratings with a probit model and funds flow components. The Financial Review 23, 269-286.

Greene W.H., 1995. LIMDEP Version 7.0 User's Manual. Econometric Software Inc., Plainview, NY.

Greene W. H., 1997. Econometric Analysis, 3rd ed. Englewood Cliffs, NJ: Prentice-Hall.

Hand J.R.M., Holthausen R.W., Leftwich R.W. 1992. The effect of bond rating agency announcements on bond and stock prices. The Journal of Finance 67, 733-752.

Heckman J.J., 1978. Dummy endogenous variables in a simultaneous equation system. Econometrica 47, 153-161.

Heckman J., 1979. Sample selection bias as a specification error. Econometrica 47, 153-61.

Hol, S.,2007. The influence of the business cycle on bankruptcy probability. International transactions in operational research 14, 75-90.

Horrigan J.O., 1966. The determination of long term credit standing with financial ratios. Journal of Accounting Research (Suppl.), 44-62.

Jensen, M.C., Meckling W.H., 1976. Theory of the firm: managerial behaviour, agency costs and ownership structure. Journal of Financial Economics 3, 305-360.

Kao C., Wu C., 1990. Two-step estimation of linear models with ordinal unobserved variables: the case for corporate bonds. Journal of business & economic statistics 8, 317-325.

Kaplan R.S., Urwitz G. 1979. Statistical models of bond ratings: a methodological inquiry. Journal of Business 52, 231-261.

Katz, S., 1974. The price and adjustment process of bonds to rating reclassifications: a test of bond market efficiency. The Journal of Finance 29, 551-559.

Laeven L., Levine R. 2009. Bank governance, regulation and risk taking. Journal of Financial Economics 93, 259-275.

Lane W.R., Looney S.W., Wansley J.W., 1986. An application of the Cox proportional hazards model to bank failure. Journal of Banking & Finance 10, 511-531.

Li P., Seyyed F.J., Smith S.D., 1999. The independent impact of credit rating changes – The case of Moody's rating refinement on yield premiums, Journal of Business Finance and Accounting 26, 337-363.

Lucas D., Lonski J., 1992. Changes in corporate credit quality 1970–1990. Journal of Fixed Income, 7-14.

Löffler G., 2004. An anatomy of rating through the cycle. Journal of Banking & Finance 28, 695-720.

Millon M., Thakor A., 1985, Moral hazard and information sharing: A model of financial information gathering agencies. Journal of Finance 40, 1403-1422.

Morgan D.P, 2002. Rating banks: risk and uncertainty in an opaque industry. The American Economic Review 92, 874-888.

Nickell P., Perraudin W., Varotto, S., 2000. Stability of rating transitions. Journal of Banking & Finance 24, 203-227.

Ohlson, J. 1980. Financial ratios and the probalistic prediction of bankruptcy. Journal of Accounting Research 18, 109-131.

Pinches G.E., Mingo, K.A., 1973. A multivariate analysis of industrial bond ratings. Journal of Finance 28, 1-18.

Pinches, G.E., Mingo, K.A., 1975. The role of subordination and industrial bond ratings. Journal of Finance 30, 201-206.

Platt, H.D., Platt, M., 1991. A note on the use of industry-relative ratios in bankruptcy prediction. Journal of Banking and Finance 15, 1183-1194.

Pogue, T. F., Soldofsky R.M., 1969. What's in a bond rating? Journal of Financial and Quantitative Analysis 4, 201 – 28.

Poon W., Firth M., Fung H-G., 1999. A multivariate analysis of the determinants of Moody's bank financial strength ratings. Journal of International Financial Markets, Institutions and Money 9, 267-283.

Poon W., 2003a. Are unsolicited credit ratings biased downward? Journal of Banking & Finance 27, 593-614.

Poon W., 2003b. Are unsolicited bank ratings lower after controlling for financial and sovereign risk? Unpublished working paper, Lingnan University, Hong Kong.

Poon W., Firth M., 2005. Are unsolicited credit ratings lower? International evidence from bank ratings. Journal of Business Finance & Accounting 32, 1741-1761.

Pottier S.W., Sommer D.W., 1999. Property liability insurer financial strength ratings: differences across rating agencies. Journal of Risk and Insurance 66, 621-642.

Saunders A., 2002. Credit risk measurement: Value at risk and other new paradigms (2nd ed.), John Wiley and Sons, New York.

Tabakis, E., Vinci, A., 2002. Analyzing and combining multiple credit assessments of financial institutions. WP No 123, European central Bank.

Thompson G.R. and Vaz, P., 1990. Dual bond ratings: a test of the certification function of rating agencies. The Financial Review 25, 457-471.

Van Gestel T., Baesens B., Van Dijcke P., Suykens J., Garcia J., Alderweireld T., 2005. Linear and nonlinear credit scoring by combining logistic regression and support vector machines, Journal of Credit Risk 1.

Van Gestel T., Baesens B., Van Dijcke P., Garcia J., Suykens J.A.K., Vanthienen J., 2006. A process model to develop an internal rating system: sovereign credit ratings. Decision Support Systems 42, 1131-1151.

Van Gestel T., Baesens B., 2009. Credit risk management: basic concepts: financial risk components, rating analysis, models, economic and regulatory capital, Oxford University Press, ISBN 978-0-19-954511-7.

Van Roy P., 2006. Is there a difference between solicited and unsolicited bank ratings and if so, why? Working Paper 79, National Bank of Belgium.

Vink D., Thibeault A. and Fabozzi F., 2009. The determinants of credit spreads on asset-backed securitization: through-the –cycle or point-in-time credit rating? Submitted to The Journal of Credit Money and Banking.

Wilson, N., Altantlar, A., Hill, P., 2009. Insolvency risk models for non-listed companies. Working paper.

Yang Z.R., Platt M.B., Platt H.D., 1999. Probabilistic neural networks in bankruptcy prediction. Journal of Business Research 44, 67-74.

Zavgren, C.V., 1985. Assessing the vulnerability to failure of American industrial firms: a logistic analysis. Journal of Business Finance and Accounting 12, 19-45.

Tables

Year	Mean S&P	Mean Moody's
2000	6.12	4.93
2001	6.06	4.84
2002	6.23	4.90
2003	6.24	5.06
2004	6.18	5.04
2005	6.07	5.16
2006	5.33	5.30
2007	5.27	4.85
2008	5.42	5.15
2009	5.55	5.82

Table 3.1: Mean bank ratings S&P and Moody's full cover December 2000-2009[68]

The above table shows that on average Moody's assigns lower, thus more favourable bank ratings than S&P, with the exception of the year 2009.

Year	Mean S&P	Mean Moodys
2000	5,58	4,96
2001	5,67	4,85
2002	5,97	4,87
2003	6,00	4,92
2004	5,90	4,90
2005	5,84	4,89
2006	5,59	4,88
2007	5,37	4,25
2008	5,81	4,49
2009	6,26	5,33

Table 3.2: Mean bank ratings S&P and Moody's banks with 2 ratings December 2000-2009[69]

The above table shows that for banks that are rated by both Moody's and S&P, on average Moody's assigns lower, thus more favourable bank ratings than S&P.

[68] We have recoded the S&P and Moody's bank ratings to a 1-17 scale with 1 being AAA/Aaa. As such a lower rating scale should be interpreted as a better rating.
[69] We have recoded the S&P and Moody's bank ratings to a 1-17 scale with 1 being AAA/Aaa. As such a lower rating scale should be interpreted as a better rating.

Consolidated statement dummy (1 when consolidated, 0 otherwise)
Qualified statement dummy (1 when qualified, 0 otherwise)
Specialisation dummy (1 when commercial, 0 otherwise)
Liquidity
Interbank ratio
Liquid Assets to Customer ST Fund
Liquid Assets to Deposits and Borrowing
Liquid Assets to Total Assets
Bank Deposits to Total Assets
Liquid Assets to Deposits
Loan to Total Assets
Deposits to Total Assets
Net Loan to Total Assets
Loan to deposits
Profitability
ROE (Net Income to Equity)
ROA (Operating Income to Assets)
Net Interest Margin
Cost to Income
Solvency
Equity to Total Assets
Equity to Liability
Equity to Risky Assets
Core Capital to Equity
Common Equity to Total Assets
Equity to Loans
Asset quality
Loan Loss Provisions to Assets
Loan Loss Provisions to Net Interest Revenue
Loan Loss Provisions to Loans
Risky Assets to Total assets
Operational Efficiency
Overhead to Total Assets
Overhead to Total Expenses
Operational Expenses to Total Assets
Operational Expenses to Total Expenses
Total Expenses to Total Assets

Table 3.3: Financial variables included in analysis

	Countryname
1	AUSTRIA
2	BELARUS
3	BELGIUM
4	BULGARIA
5	CANADA
6	CROATIA
7	CYPRUS
8	CZECH REPUBLIC
9	DENMARK
10	ESTONIA
11	FINLAND
12	FRANCE
13	GERMANY
14	GREECE
15	HUNGARY
16	ICELAND
17	IRELAND
18	ITALY
19	LATVIA
20	LIECHTENSTEIN
21	LITHUANIA
22	LUXEMBOURG
23	MALTA
24	MONACO
25	NETHERLANDS
26	NORWAY
27	POLAND
28	PORTUGAL
29	ROMANIA
30	RUSSIAN FEDERATION
31	SLOVAKIA
32	SLOVENIA
33	SPAIN
34	SWEDEN
35	SWITZERLAND
36	UKRAINE
37	UNITED KINGDOM
38	USA

Table 3.4: Different countries represented in sample

Bank Concentration	Deposits held by 5 largest banks
Capital regulation index *Initial capital stringency	 Are the sources of funds to be used as capital verified by the regulatory/supervisory authorities? Can the initial disbursement or subsequent injections of capital be done with assets other than cash or government securities? Can initial disbursement of capital be done with borrowed funds?
*Overall capital stringency	Is this ratio risk weighted in line with the 1988 Basle guidelines? Does the minimum ratio vary as a function of market risk? What fraction of revaluation gains is allowed as part of capital? (<75% ➔ 1) Before minimum capital adequacy is determined, which of the following are deducted from the book value of capital? (unreal loss in securities, unreal foreign exchanges losses, MV of loan losses not realized in accounting books)
Diversification and liquidity index	Are there explicit, verifiable, and quantifiable guidelines regarding asset diversification? Are banks prohibited from making loans abroad? Are banks required to hold either liquidity reserves or any deposits at the Central Bank?
Accounting disclosure and director liability	Does accrued, though unpaid, interest/principal enter the income statement while the loan is still performing? Are financial institutions required to produce consolidated accounts covering all bank and any non-bank financial subsidiaries? Are bank directors legally liable if information disclosed is erroneous or misleading?

Table 3.5: Data Barth et al. (2001, 2003, 2008)

Variables S&P rated banks	Mean	Std.Dev.	Min	Max
S&P rating Dec	3,01	0,84	1,00	7,00
a3ylnassets	7,30	2,46	0,98	14,75
Specialisation dummy			0,00	1,00
Consolidation dummy			0,00	1,00
Audited Statement Dummy			0,00	1,00
Liquidity				
a3y Interbank ratio	123,45	107,14	0,00	424,89
a3y Liquid Assets to Customer ST Fund	20,60	14,83	0,00	62,64
a 3y Liquid Assets to Deposits and Borrowing	17,98	12,49	0,00	52,35
a3y Liquid Assets to Total Assets	0,14	0,11	0,00	1,00
a3y Bank Deposits to Total Assets	0,11	0,09	0,00	0,99
a3y Liquid Assets to Deposits	0,23	0,17	0,00	0,77
a3y Loan to Total Assets	0,59	0,18	0,11	1,00
a3y Deposits to Total Assets	0,76	0,20	0,08	1,00
a3y Net Loan to Total Assets	0,58	0,18	0,10	0,99
a3y Loan to deposits	1,38	4,43	0,00	99,75
Profitability				
a3y ROE (Net Income to Equity)	0,07	0,05	-0,14	0,29
a3y ROA (Operating Income to Assets)	0,01	0,00	-0,01	0,02
a3y Net Interest Margin	2,65	1,02	0,04	5,64
a3y Cost to Income	0,67	0,14	0,21	1,16
Solvency				
a3y Equity to Total Assets	0,08	0,07	-0,30	0,89
a3y Equity to Liability	7,71	3,48	-2,50	16,43
a3y Equity to Risky Assets	0,15	1,56	-0,38	134,48
a3y Core Capital to Equity	0,10	0,08	0,38	0,97
a3y Common Equity to Total Assets	0,08	0,07	-0,34	0,97
a3y Equity to Loans	0,42	2,45	-0,53	49,18
Asset quality				
a3y Loan Loss Provisions to Assets	0,004	0,003	-0,0087	0,019
a3y Loan Loss Provisions to Net Interest Revenue	0,17	0,13	-0,36	0,73
a3y Loan Loss Provisions to Loans	0,01	0,01	-0,02	0,03
a3y Risky Assets to Total assets	0,82	0,12	0,00	1,00
Operational Efficiency				
a3y Overhead to Total Assets	0,03	0,05	0,00	1,77
a3y Overhead to Total Expenses	0,43	0,15	0,00	0,99
a3y Operational Expenses to Total Assets	0,06	0,01	0,02	0,10
Country Variables				
Capital regulation index	6,07	0,79	2,00	9,00
Diversification and Liquidity Index	1,69	0,95	0,00	3,00
Accounting Disclosure	2,50	0,50	0,00	3,00
Foreign Sovereign rating S&P	1,40	1,88	1,00	17,00
Corruption Index	7,43	1,08	0,00	10,00

Table 3.6: Descriptives S&P rated banks

Variables Moody's rated banks	Mean	Std.Dev.	Min	Max
Moody’s rating Dec	5,10	2,70	1,00	17,00
a3ylnassets	9,66	2,06	3,06	14,75
Specialisation dummy			0,00	1,00
Consolidation dummy			0,00	1,00
Audited Statement Dummy			0,00	1,00
Liquidity				
a3y Interbank ratio	669,55	1171,69	0,02	6499,22
a3y Liquid Assets to Customer ST Fund	32,86	32,80	0,00	125,13
a 3y Liquid Assets to Deposits and Borrowing	21,69	20,34	0,00	85,63
a3y Liquid Assets to Total Assets	0,17	0,18	0,00	0,89
a3y Bank Deposits to Total Assets	0,21	0,15	0,00	0,95
a3y Liquid Assets to Deposits	0,38	0,38	0,00	1,37
a3y Loan to Total Assets	0,60	0,23	0,00	0,99
a3y Deposits to Total Assets	0,60	0,20	0,00	0,96
a3y Net Loan to Total Assets	0,58	0,23	0,00	0,99
a3y Loan to deposits	1,14	0,92	0,00	9,91
Profitability				
a3y ROE (Net Income to Equity)	0,11	0,08	-0,14	0,38
a3y ROA (Operating Income to Assets)	0,01	0,01	-0,02	0,04
a3y Net Interest Margin	2,62	2,06	-3,60	10,32
a3y Cost to Income	0,74	0,34	-0,19	1,76
Solvency				
a3y Equity to Total Assets	0,09	0,08	-0,28	0,97
a3y Equity to Liability	8,97	5,68	-10,43	25,83
a3y Equity to Risky Assets	0,15	1,56	-0,38	134,48
a3y Core Capital to Equity	0,10	0,08	0,38	0,97
a3y Common Equity to Total Assets	0,08	0,08	-0,28	0,98
Asset quality				
a3y Loan Loss Provisions to Assets	0,00	0,00	-0,01	0,02
a3y Loan Loss Provisions to Net Interest Revenue	0,16	0,17	-0,39	0,73
a3y Loan Loss Provisions to Loans	0,01	0,01	-0,02	0,03
a3y Risky Assets to Total assets	0,79	0,19	0,00	1,00
Operational Efficiency				
a3y Overhead to Total Assets	0,02	0,03	0,00	0,56
a3y Overhead to Total Expenses	0,38	0,21	0,00	1,00
a3y Operational Expenses to Total Assets	0,05	0,02	0,00	0,12
Country Variables				
Capital regulation index	5,95	1,22	2,00	9,00
Diversification and Liquidity Index	2,01	0,85	0,00	3,00
Accounting Disclosure	2,85	0,36	0,00	3,00
Foreign Sovereign rating Moody’s	2,23	3,09	1,00	17,00
Corruption Index	7,15	1,72	0,00	10,00

Table 3.7: Descriptives Moody’s rated banks

Year	S&P full rating sample	S&P our sample US-EU	% cover	Mean	Moody’s full rating sample	Moody’s our sample US-EU	%cover	Mean
2000	1276	572	45.9%	6.12	828	346	41.2%	4.93
2001	1264	594	47%	6.06	839	359	42.8%	4.84
2002	1264	599	47.4%	6.23	826	365	44.2%	4.90
2003	1267	610	48.1%	6.24	857	384	44.8%	5.06
2004	1280	610	47.7%	6.18	885	413	46.7%	5.04
2005	1317	612	46.5%	6.07	945	449	47.5%	5.16
2006	2672	1747	65.4%	5.33	1005	479	47.6%	5.30
2007	2698	1738	64.4%	5.27	1054	506	48%	4.85
2008	2666	1701	63.8%	5.42	1055	502	47.5%	5.15
2009	2606	1668	64%	5.55	1024	486	47.5%	5.82

Table 3.8: Overview S&P and Moody’s cover in December

	All banks Moody's	All banks S&P	Banks only Moody's rating	Banks only S&P ratings	Moodys banks with 2 ratings	S&P banks with 2 ratings	Banks with 2 ratings at the same time
	680	2046	293	1659	387	387	208
2000	346	572	101	295	245	277	210
2001	359	594	111	316	248	278	207
2002	365	599	120	315	245	284	212
2003	384	610	131	320	253	290	218
2004	413	610	151	323	262	287	218
2005	449	612	169	323	280	289	234
2006	479	1747	191	1455	288	292	242
2007	506	1738	201	1449	305	289	255
2008	502	1701	199	1419	303	282	250
2009	486	1668	185	1396	301	272	243

Table 3.9: Overview of different number of banks in sample

Moody's - S&P	Jan 09 Freq	%	Apr 09 Freq	%	Dec 09 freq	%
-8			1	0.4%		
-7						
-6	2	0.8%				
-5			1	0.4%		
-4	4	1.6%	1	0.4%	3	1.23%
-3	33	13.2%	25	10.12%	25	10.29%
-2	80	32%	85	34.41%	73	30.04%
-1	71	28.4%	59	23.89%	62	25.51%
0	41	16.4%	37	14.98%	40	16.46%
1	13	5.2%	24	9.72%	27	11.11%
2	3	1.2%	8	3.24%	5	2.06%
3					3	1.23%
4					1	0.41%
5			2	0.81%	1	0.41%
6	1	0.4%	1	0.40%	1	0.41%
7	1	0.4%	2	0.81%	1	0.41%
8	1	0.4%	1	0.40%	1	0.41%

Table 3.10: Rating differences Moody's – S&P

	Distribution of Moody's relative to S&P Jan09	Distribution of Moody's relative to S&P Dec 09
% rated lower (better)	76%	67%
% rated same	16,4%	16,5%
% rated higher (worse)	7,6%	16,5%
Average diff in rating notches	1,59	1,53

Table 3.11: Rating differences between agencies summary

	a3y eqtoliab	**a3y lnass**	**a3y opexpTA**	**a3y liqassTA**	**Sov Rating**	**a3y LLP to L**	**a3y Cost-to-inc**
a3yc eq to liab	1						
a3y lnassets	-0.3627	1					
a3y operatexp TA	0.3303	-0.3329	1				
a3y liqass to TA	0.0166	-0.1397	-0.0560	1			
Sovereign rating Moodys	0.2795	-0.4309	0.3483	0.1214	1		
a3y LLP to Loans	-0.0347	-0.0130	-0.0499	0.0021	-0.0261	1	
a3y Cost-to-inc	-0.1467	0.3343	-0.3296	0.0282	-0.0046	-0.0504	1

Table 3.12: Correlation table final regression S&P

	a3y cost-to-inc	**a3y lnass**	**S&P sov rating**	**a3y LLP to L**	**a3y LiqAssD&B**	**lnzindex3y**	**a3y eqta**
a3y cost-to-inc	**1**						
a3y lnassets	-0.1959	1					
S&P sovereign rating	-0.0046	-0.0790	1				
a3y LLP to Loans	0.0023	-0.0616	0.0431	1			
a3y LiqAss to Dep&Bor	0.1603	0.1478	0.2387	-0.0529	1		
lnzindex3y	-0.0690	-0.2173	-0.1053	0.0260	-0.1519	1	
a3y eqta	-0.1624	-0.1184	0.0589	0.0883	0.1270	-0.0396	1

Table 3.13: Correlation table final regression Moody's

	S&P Dec Baseline 3-year averages	S&P Dec Baseline 5-year averages
Variable	**Estimate**	**Estimate**
Cost to Income	5.196776*** *(0.000)*	4.687133*** *(0.000)*
Ln assets	-0.6194814*** *(0.000)*	-0.7901151*** *(0.000)*
Equity to TA	-5.118269*** *(0.000)*	-3.943429*** *(0.001)*
Loan loss provisions to loans	4.601818** *(0.040)*	8.928692*** *(0.001)*
Liquid assets to deposits and ST borrowing	-0.028153*** *(0.000)*	-0.0512166*** *(0.000)*
Lnzindex3y	-0.1336408** *(0.022)*	-0.3728674*** *(0.000)*
Foreign sovereign S&P	1.347701*** *(0.000)*	1.546909*** *(0.000)*
Log Likelihood	-2512.2881	-2032.0832
Level 2 variance (spid)	26.919597	29.024486
Level 3 variance(country)	2.125618	2.2976029

Table 3.14: Model Output S&P Long

The above table reports the results of the S&P random intercept logistic regression for the period 2000 to 2009 including 3-year and 5-year averages of the financial variables.

	S&P Dec Including Trend and Recession Index	S&P Dec Including Trend and yield curve	S&P Dec Including Trend Inflation	S&P Dec Including Trend and Employment Growth
Variable	**Estimate**	**Estimate**	**Estimate**	**Estimate**
Cost to Income	5.489887*** *(0.000)*	5.722678*** *(0.000)*	5.062131*** *(0.000)*	7.079094*** *(0.000)*
Ln assets	-0.4562176*** *(0.000)*	-0.4676049*** *(0.000)*	-0.531818*** *(0.000)*	-0.6966713*** *(0.000)*
Equity to TA	-1.547696* *(0.098)*	-1.431066 *(0.128)*	2,721595 *(0.275)*	-1.35696*** *(0.004)*

Loan loss provisions to loans	5.079919** *(0.012)*	4.844494 *(0.113)*	5,80232*** *(0.000)*	2.480321 *(0.113)*
Liquid assets to deposits and ST borrowing	-0.0298485*** *(0.000)*	-0.0331123*** *(0.000)*	-0.0241177*** *(0.000)*	-0.039397*** *(0.000)*
Lnzindex3y	-0.1249129** *(0.033)*	-0.1390435** *(0.019)*	-0.1379403** *(0.013)*	-0.2086796*** *(0.007)*
Foreign sovereign S&P	1.203286*** *(0.000)*	0.9449514*** *(0.000)*	1.402741*** *(0.000)*	1.142884*** *(0.000)*
Trend	-0.0622416 *(0.160)*	-0.0283421 *(0.428)*	-0.0220932 *(0.566)*	-0.0417937 *(0.280)*
Business Cycle Indicator	-0.2661059 *(0.187)*	-0.0022072 *(0.429)*	0.0045229 *(0.438)*	0.1126366 *(0.246)*
Log Likelihood	-2505.8216	-2443.4244	-2520.0695	-2235.0821
Level 2 variance (spid)	27.824913	28.041591	28.138581	27.585942
Level 3 variance(country)	3.5233082	3.4384507	0.91972696	1.925792

Table 3.15: Model Output S&P Long including trend and business cycle indicator

The above table reports the results of the S&P random intercept logistic regression for the period 2000 to 2009 including 3-year averages of the financial variables, a trend and a business cycle indicator.

	Moody's Dec Baseline 3-year averages	**Moody's Dec Baseline 5-year averages**
Variable	**Estimate**	**Estimate**
Cost to Income	.5994322*** *(0.005)*	0.4361869*** *(0.000)*
Ln assets	-1.058399*** *(0.000)*	-0.3796626** *(0.000)*
Equity to liability	-0.088408*** *(0.000)*	0.0108524 *(0.662)*
Loan loss provisions to loans	0.0698032*** *(0.000)*	0.1042066*** *(0.002)*
Liquid assets to TA	-3.911369*** *(0.000)*	-3.734909*** *(0.000)*
Operational Exp to TA	46.01728*** *(0.000)*	60.79261*** *(0.000)*

Foreign sovereign Moody's	0.8765789*** *(0.000)*	1.132645*** *(0.000)*
Trend		
Recession Index		
Log Likelihood	-1438.4703	-1335.6296
Level 2 variance (spid)	12.53144	15.049626
Level 3 variance(country)	3.8184876	2.7645005

Table 3.16: Model Output Moody's Long

The above table reports the results of the Moody's random intercept logistic regression for the period 2000 to 2009 including 3-year and 5-year averages of the financial variables.

	Moody's Dec including trend and recession index	**Moody's Dec including trend and slope of the yield curve**	**Moody's Dec including trend and inflation**	**Moody's Dec including trend and employment growth**
Variable	**Estimate**		**Estimate**	**Estimate**
Cost to Income	0.0686342 *(0.794)*	-0.1672576 *(0.500)*	0.0019822 *(0.992)*	0.9038672*** *(0.001)*
Ln assets	-0.5462733*** *(0.000)*	-1.150998*** *(0.000)*	-1.180972*** *(0.000)*	-0.699192*** *(0.000)*
Equity to liability	0.0389776 *(0.141)*	-0.0604277** *(0.015)*	-0.0277749 *(0.387)*	0.0469887 *(0.051)*
Loan loss provisions to loans	0.0852536*** *(0.000)*	0.0689337*** *(0.000)*	0.0659441*** *(0.000)*	0.0825072*** *(0.000)*
Liquid assets to TA	-4.363802*** *(0.000)*	-5.83761*** *(0.000)*	-6.247318*** *(0.000)*	-5.646693*** *(0.000)*
Operational Exp to TA	56.03593*** *(0.000)*	39.1876*** *(0.000)*	45.17666*** *(0.000)*	52.60868*** *(0.000)*
Foreign sovereign Moody's	1.299636*** *(0.000)*	1.047297*** *(0.000)*	0.8984238*** *(0.000)*	1.607647*** *(0.000)*
Trend	-0.1862029*** *(0.001)*	-0.2721508*** *(0.000)*	-0.345014*** *(0.000)*	-0.2346926*** *(0.000)*
Business cycle indicator	0.2979241 *(0.199)*	0.0078845** *(0.046)*	0.0134082* *(0.067)*	-0.1889426** *(0.014)*
Log Likelihood	-1421.0114	-1318.8795	-1416.9092	-1249.0864
Level 2 variance (spid)	14.70757	12.017845	13.055482	16.317541

Level 3 variance(country)	2.5685926	1.8165813	1.5047985	2.5098084

Table 3.17: Model Output Moody's Long including trend and business cycle indicator

The above table reports the results of the Moody's random intercept logistic regression for the period 2000 to 2009 including 3-year averages of the financial variables, a trend and a business cycle indicator.

	Moody's Dec including trend and slope of the yield curve	**Moody's Dec including trend and inflation**	**Moody's Dec including trend and employment growth**
Variable	**Estimate**	**Estimate**	**Estimate**
Cost to Income	0.6745675 *(0.169)*	1.416424*** *(0.000)*	1.838931*** *(0.000)*
Ln assets	-1.042867*** *(0.000)*	-0.7708857*** *(0.000)*	-1.344302*** *(0.000)*
Equity to liability	-0.0596341** *(0.013)*	0.0034049 *(0.927)*	-0.0732229*** *(0.002)*
Loan loss provisions to loans	0.0037361 *(0.900)*	0.0181854 *(0.560)*	0.0093974 *(0.781)*
Liquid assets to TA	-7.077562 *(0.000)*	-6.416664*** *(0.000)*	-4.332611*** *(0.000)*
Operational Exp to TA	24.76133*** *(0.002)*	46.58874*** *(0.000)*	26.78743*** *(0.000)*
Foreign sovereign Moody's	1.037197*** *(0.000)*	1.000502*** *(0.000)*	0.9131326*** *(0.000)*
Trend	0.0227778 *(0.925)*	-0.0880097 *(0.736)*	-0.0581661 *(0.826)*
Business cycle indicator	-0.0068495* *(0.081)*	0.0125266 *(0.124)*	-0.2653421*** *(0.005)*
Cost to income-yearly mean	2.493567 *(0.115)*	2.24924 *(0.133)*	2.169972 *(0.210)*
Ln assets-yearly mean	2.895603 *(0.288)*	3.976279 *(0.213)*	4.304057 *(0.192)*
Eq to liab – yearly mean	2.699987** *(0.013)*	2.889452** *(0.012)*	3.43646* *(0.060)*
LLP to Loans-yearly	-0.08475437***	-0.873141**	-1.032958***

mean	(0.006)	*(0.014)*	*(0.006)*
Liq ass to TA- yearly mean	-82.77463 *(0.305)*	-105.9233 *(0.255)*	-101.9383 *(0.285)*
Oper Exp to TA- yearly mean	-98.4135 *(0.000)*	-93.95716*** *(0.000)*	-140.6661*** *(0.000)*
Log Likelihood	-1304.4894	-1400.1572	-1225.2254
Level 2 variance (spid)	11.630321	13.738704	16.123937
Level 3 variance(country)	2.2258986	3.1082928	6.2207045

Table 3.18: Model Output Moody's Long including trend and business cycle indicator and yearly means of financial averages

The above table reports the results of the Moody's random intercept logistic regression for the period 2000 to 2009 including 3-year averages of the financial variables, a trend, a business cycle indicator and the time series of the yearly cross-sectional averages of the included financial variables.

	S&P Jan '09 3-year averages	**S&P Jan '09 5-year averages**		**Moody's Jan '09 3-year averages**	**Moody's Jan '09 5-year averages**
Variable	**Estimate**	**Estimate**	**Variable**	**Estimate**	**Estimate**
Cost to Income	5.819897*** *(0.000)*	5.171667*** *(0.000)*	Ln assets	-0.4776386*** *(0.000)*	-0.4893602*** *(0.000)*
Ln assets	-0.1958357 *** *(0.000)*	-0.1792552*** (0.001)	Equity to Liab	-0.0611345** *(0.021)*	-0.0602759** *(0.023)*
Equity to TA	-3.884725 ** *(0.019)*	-4.064304 ** *(0.016)*	Oper exp to TA	29.55236*** *(0.000)*	23.22541*** *(0.000)*
Loan loss provisions to loans	65.62607*** *(0.000)*	57.44782 *** *(0.003)*	Liquid assets to TA	-1.414359* *(0.076)*	-1.160614 *(0.164)*
Liquid assets to deposits and ST borrowing	-0.0328701 *** *(0.000)*	-0.0300719*** *(0.000)*	Diversification and Liquidity index	-0.9640177*** *(0.000)*	-0.9511796*** *(0.000)*
Lnzindex3y	-0.2410697 *** *(0.001)*	-0.2742442*** *(0.000)*			
Foreign sovereign S&P	0.7462133*** *(0.000)*	0.7226036 *** *(0.000)*			
Log Likelihood	-581.49252	-595.13968	**Log Likelihood**	-361.55339	-372.72482

Level 2 variance (country)	0.8501679	0.87666464	**Level 2 variance (country)**	0.43270066	0.37352643

Table 3.19: Output S&P and Moody's cross-sectional 1-7

The above table reports the results of the S&P and Moody's cross sectional analysis for the year 2009 including 3-year and 5-year averages of the financial variables.

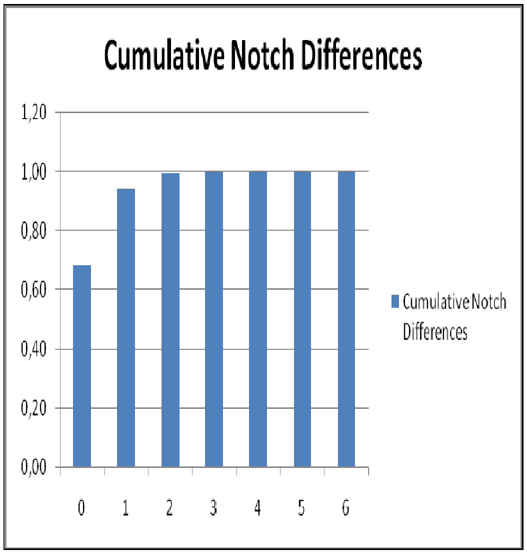
S&P	**S&P**	**Moody's**	**Moody's**
S&P Rating Jan 09	**Estimate**	**Moodys Rating Jan 09**	**Estimate**
Cost to Income	3.148795*** *(0.000)*	Ln assets	-0.2524702*** *(0.000)*
Ln assets	-.0913528*** *(0.000)*	Equity to Liab	-0.0348663*** *(0.009)*
Equity to TA	-1.408312* *(0.098)*	Oper exp to TA	16.9863*** *(0.000)*
Loan loss provisions to loans	49.37193*** *(0.000)*	Liquid assets to TA	-0.6980036* *(0.095)*
Liquid assets to deposits and ST borrowing	-0.0182327*** *(0.000)*	Diversification and Liquidity index	-0.6124702*** *(0.000)*
Lnzindex3y	-0.1661964*** *(0.000)*		
Foreign sovereign S&P	0.3779692*** *(0.000)*		
Selection		**Selection**	
Cost to Income	-1.331666*** *(0.006)*	Cost to Income	-0.072279 *(0.773)*
Fix assets to TA	27.21285*** *(0.001)*	Fix assets to TA	-3.037997 *(0.682)*
Ln assets	0.5561019*** *(0.000)*	Ln assets	0.3349411*** *(0.000)*
Quoted	0.3714975** *(0.012)*	Quoted	0.4762711*** *(0.008)*
Loan to TA	0.7918258** *(0.016)*	Loan to TA	-0.1300985 *(0.719)*
Debt to Eq	0.0007764 *0.652*	Debt to Eq	-8.30e-06 *(0.954)*

Log Likelihood	-844.87005	**Log Likelihood**	-549.27385
Likelihoodratio for rho=0	Chi2 (1) = 5.49 Prob>=chi2= 0.019	**Likelihoodratio for rho=0**	Chi2 (1) = 0.54 Prob>=chi2=0.464

Table 3.20: Sample Selection Model

The above table reports the S&P and Moody's sample selection model for banks that receive a rating from both rating agencies.

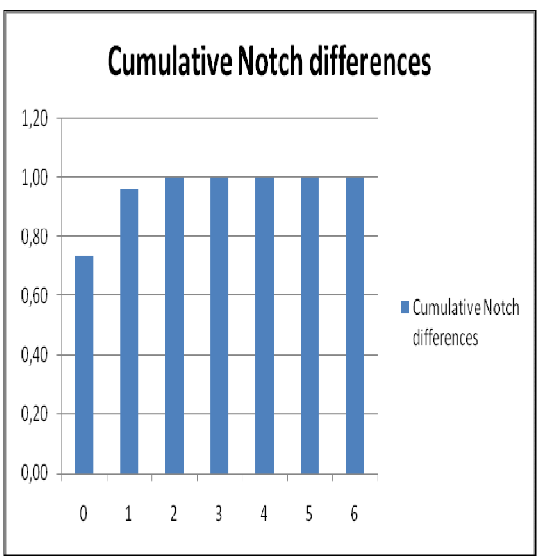
Figures



	Cumulative Notch Differences
0	68.32%
1	94.21%
2	99.57%
3	99.86%
4	100%
5	100%
6	100%

Figure 3.1: Notch Differences S&P Long 1-7 (3-year averages)

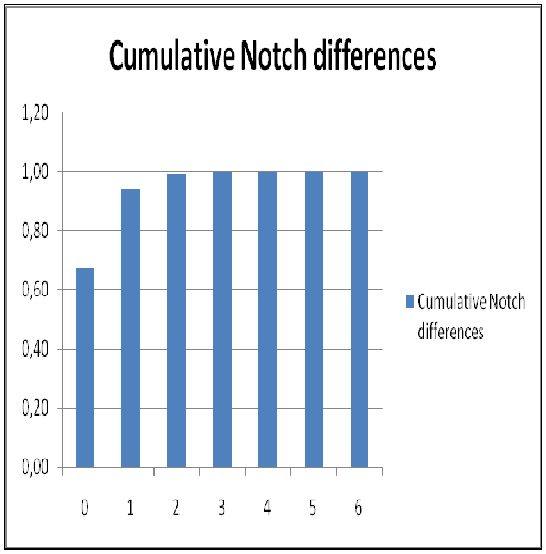
The above figure and table report the out-of-sample notch differences for the S&P model including 3-year averages. The histogram shows the cumulative accuracy for increasing notch differences between the true S&P rating and the rating estimated by the model.



	Cumulative Notch differences
0	73.44%
1	95.68%
2	99.71%
3	99.88%
4	100%
5	100%
6	100%

Figure 3.2: Notch Differences S&P Long 1-7 (5-year averages)

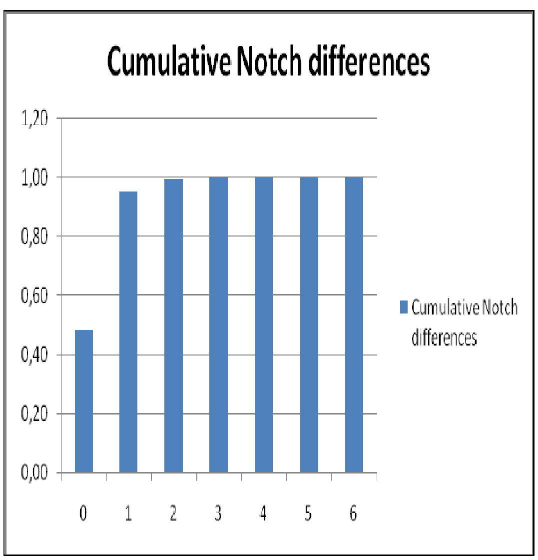
The above figure and table report the out-of-sample notch differences for the S&P model including 5-year averages. The histogram shows the cumulative accuracy for increasing notch differences between the true S&P rating and the rating estimated by the model.



	Cumulative Notch differences
0	67.52%
1	94.02%
2	99.13%
3	99.86%
4	100%
5	100%
6	100%

Figure 3.3: Notch Differences S&P Long 1-7 (3-year averages including trend and recession index)

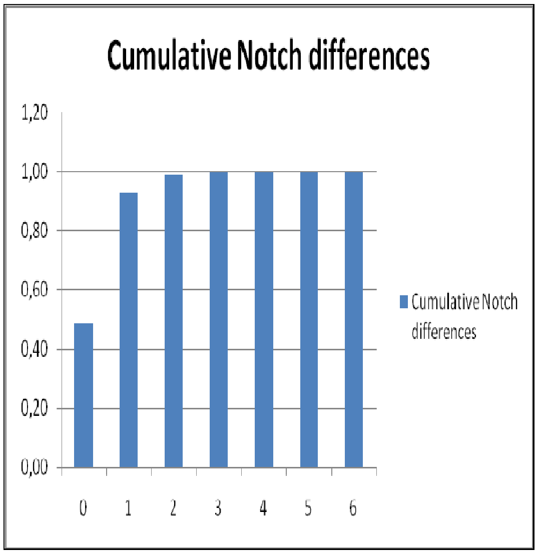
The above figure and table report the out-of-sample notch differences for the S&P model including 3-year averages, trend and recession index. The histogram shows the cumulative accuracy for increasing notch differences between the true S&P rating and the rating estimated by the model.



	Cumulative Notch differences
0	48.55%
1	95.10%
2	99.55%
3	99.87%
4	99.89%
5	100%
6	100%

Figure 3.4: Notch Differences Moody's Long 1-7 (3-year averages)

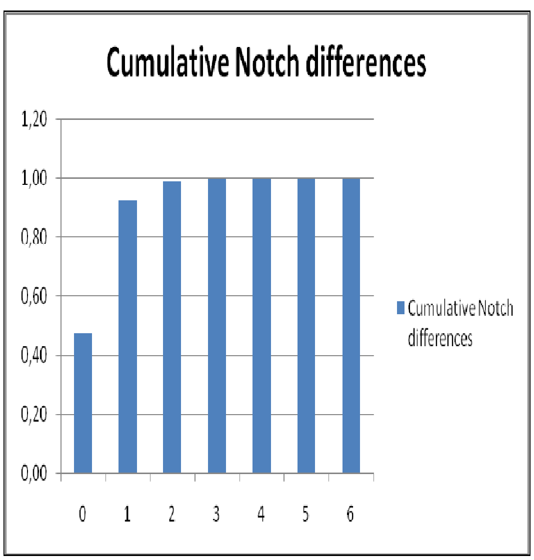
The above figure and table report the out-of-sample notch differences for the Moody's model including 3-year averages. The histogram shows the cumulative accuracy for increasing notch differences between the true Moody's rating and the rating estimated by the model.



	Cumulative Notch differences
0	48.66%
1	92.94%
2	98.66%
3	99.88%
4	100%
5	100%
6	100%

Figure 3.5: Notch Differences Moody's Long 1-7 (5-year averages)

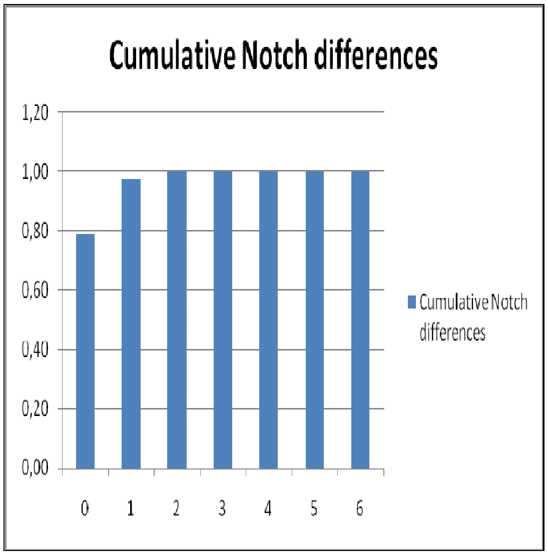
The above figure and table report the out-of-sample notch differences for the Moody's model including 3-year averages. The histogram shows the cumulative accuracy for increasing notch differences between the true Moody's rating and the rating estimated by the model.



	Cumulative Notch differences
0	47.44%
1	92.65%
2	99.11%
3	99.89%
4	99.89%
5	100%
6	100%

Figure 3.6: Notch Differences Moody's Long 1-7 (3-year averages including trend and recession index)

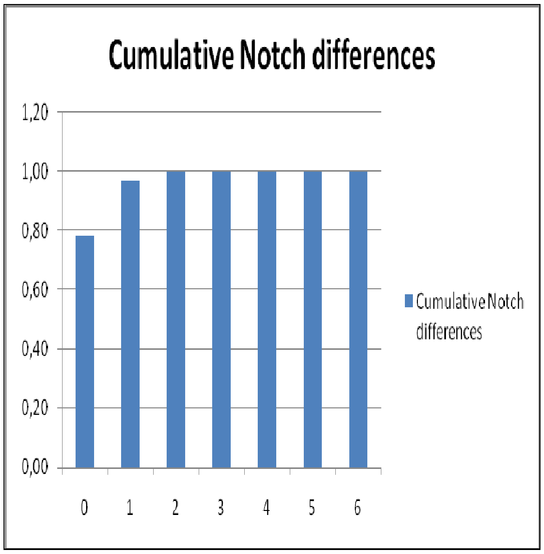
The above figure and table report the out-of-sample notch differences for the Moody's model including 3-year averages, trend and recession index. The histogram shows the cumulative accuracy for increasing notch differences between the true Moody's rating and the rating estimated by the model.



	Cumulative Notch differences
0	78.61%
1	97.36%
2	100%
3	100%
4	100%
5	100%
6	100%

Figure 3.7: Notch Differences S&P Cross Sectional 1-7 (3-year averages)

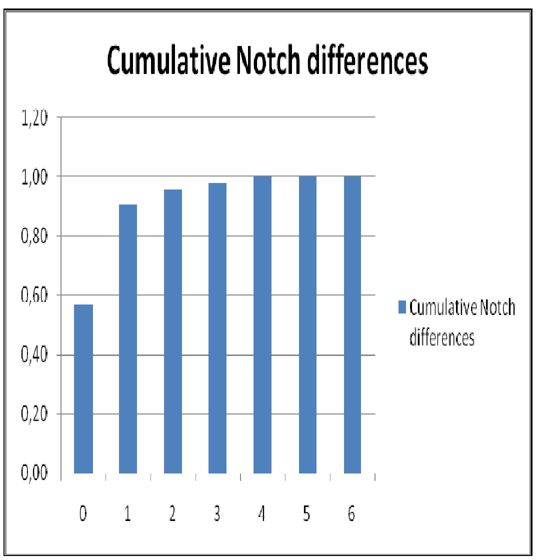
The above figure and table report the out-of-sample notch differences for the S&P model including 3-year averages. The histogram shows the cumulative accuracy for increasing notch differences between the true S&P rating and the rating estimated by the model.



	Cumulative Notch differences
0	78.42%
1	97.12%
2	100%
3	100%
4	100%
5	100%
6	100%

Figure 3.8: Notch Differences S&P Cross Sectional 1-7 (5-year averages)

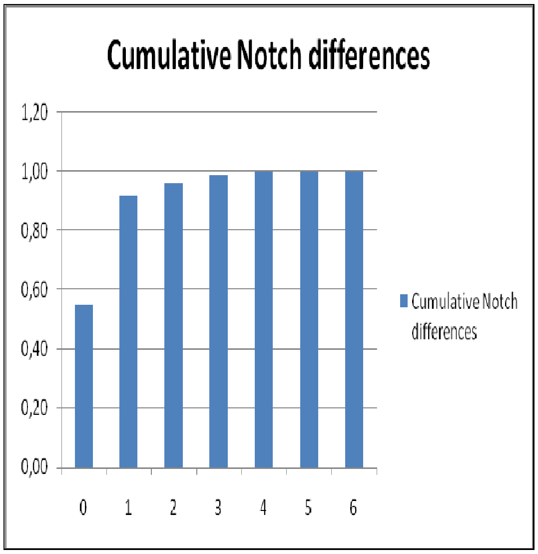
The above figure and table report the out-of-sample notch differences for the S&P model including 5-year averages. The histogram shows the cumulative accuracy for increasing notch differences between the true S&P rating and the rating estimated by the model.



	Cumulative Notch differences
0	56.55%
1	90.34%
2	95.86%
3	97.93%
4	100%
5	100%
6	100%

Figure 3.9: Notch Differences Moody's Cross Sectional 1-7 (3-year averages)

The above figure and table report the out-of-sample notch differences for the Moody's model including 3-year averages. The histogram shows the cumulative accuracy for increasing notch differences between the true Moody's rating and the rating estimated by the model.



	Cumulative Notch differences
0	55.03%
1	91.95%
2	95.97%
3	98.65%
4	100%
5	100%
6	100%

Figure 3.10: Notch Differences Moody's Cross Sectional 1-7 (5-year averages)

The above figure and table report the out-of-sample notch differences for the Moody's model including 5-year averages. The histogram shows the cumulative accuracy for increasing notch differences between the true Moody's rating and the rating estimated by the mod

General Conclusion

Over the past decade the economic environment has been characterised by high-profile business scandals in which different company stakeholders were involved. As a result, the concern surrounding risk management and focus on it have increased dramatically. Moreover, the latest crisis and recession call for enhanced risk management practices with more stringent laws and regulations. This is especially true for financial institutions, whose insolvency might result in substantial losses with huge spill-over effects to different parts of the economy. Financial institutions play a crucial role in today's globalized economy and as a consequence of different developments and various impulses, their risk profile has evolved dramatically, making the financial system much more vulnerable to macro-economical shocks. In light of the recent developments, this dissertation is contributing to the fundamentals of capital regulation of financial institutions and the use of internal and external ratings in that respect.

The latest crisis has revealed that the Basel II focus on making prudential capital more closely aligned to the banks' own economic capital, could not offset the implosion of the financial system. Furthermore, it became clear that pre-crisis capital standards were too weak for the types of risk that emerged. As a consequence, the Basel Committee is now working on a Basel III accord, whose ultimate goal is to fundamentally strengthen global capital standards. The question of course remains whether the suggested changes will address the gaps in Basel II in a sufficient and accurate way.

The first chapter of this dissertation focuses on capital requirements as the foundation of bank regulation. More specifically, we look at whether and how European banks adjust their behaviour in line with the regulatory framework. Based on several interviews with different bank stakeholders, we develop an understanding of current practices with respect to risk management, internal rating models, regulatory and economic capital, Basel II implementation and Basel III expectations. In doing so, we are addressing another objective of the Basel accords, the creation of a level playing field.

Based on our interviews it is clear that Basel II has been a first step in the right direction. Basically all parties agree that it has played an important role in the evolution of risk management, mainly by the introduction of internal models and pillar 2 economic capital. European banks seem to move in the same direction for regulatory capital, however for economic capital practices there is still a long way to go and the room for regulatory capital arbitrage remains to exist. Where Basel II has proven its strengths when it comes to risk management; in preventing downturns, the capital requirements under Basel II are considered less useful. The majority of the respondents feel that the loopholes, the scope and the room for interpretation are too big to make the Basel II regulatory framework successful.

As a result, all parties agree that a new regulation is necessary; however there is quite some disagreement on how this should be done. The choice made should consider some limitations. The new regulation should be practical, meaning that it should be possible for supervisors to control it effectively and for all banks to apply it with relative ease. The political limitations should be considered and its impact on the total welfare should be optimized. Finally, the new regulation should also be acceptable for the majority of the banks, taking into account their differences in activities, ownership structure, size etc.

It has been suggested that Basel II did not include sufficient capital requirements. Banks believe that regulatory capital should be increased, but only in a limited way. Regulators and supervisors (R&S) and academics and opinion leaders (A&Os), warn of the negative effects higher capital requirements could have on an already damaged economy. This is why capital requirements should be introduced in the long term. Even though higher capital requirements work on two levels by creating a buffer and by limiting the creation of asset bubbles, it is clear that higher capital requirements will never be sufficient when another financial crisis comes. It should only be one of many changes in the new regulation.

European bankers are mainly afraid of the impact of the new accounting and liquidity rules and they all stress the importance of a reinforced role of the supervisors. Banks believe that reinforcement and the realization of effective supervision is the main criterion for the realization of a more stable financial market. This confirms the important role our research assigns to the supervisor. One of the major difficulties will be to make a reliable estimate on how far the capabilities of supervisors go. Another difficulty on the subject of supervision is that it is still a national responsibility that will not be centralised very quickly for political reasons. A solution for this is a European coordination of supervision - the so-called level two supervision - and an increased communication and cooperation between supervisors.

We believe Basel III entails a lot of improvement, but in line with the A&Os and R&S, we feel that Basel III should look more comprehensively at the risks. In our view one of the main weaknesses in Basel III is the risk weighting of assets, which is inherently backward-looking and easy to game. The fact that banks will need to hold much more common equity than before, will probably increase the incentive to find low-risk-weight assets which can be leveraged much more than risky assets. Furthermore banks will be incentivized to increase returns without increasing measurable risk and thus will further push risk in the tails. The question of course remains whether some Basel Accord could ever really avoid this; but it’s important to keep in mind and it again stresses the crucial role of bank supervision.

We can never expect a regulation to prevent all banking crises in future, and anything which reduces its likelihood is a good thing. Our research shows that financial stability cannot be realized by one single measure, or in one single day. It will take time and will consist of many different regulations, as a result of a compromise between regulators, politicians and bankers.

Another type of financial institution that has been both victim and cause in the financial crisis are the insurance companies. Due to the Solvency II Directive, also insurance companies are currently being confronted with new regulatory requirements. One of the consequences of this planned reform will be a shift in focus to internal-based models for determining the minimum regulatory capital needed to cover unexpected losses. In the second chapter of this dissertation, we develop a simple and intuitive credit rating model with a high degree of accuracy and reliability for the European corporate exposures of an insurance company.

Taking into account the limited data and modelling experience of most insurance companies, combined with the fact that external ratings have proven to be a reasonably good indicator of corporate credit quality, we suggest exploiting the expertise of external rating agencies by mimicking their ratings. It is often argued that internal rating systems differ a lot from the systems used by external agencies and that, as a result, the mapping becomes unstable. By combining credit scoring and mapping in one exercise, we have addressed some of the potential biases and instability issues that might arise.

After thorough analysis, we find a logit model including six variables. The major strands of intuition that run through most of previous academic literature are confirmed in this chapter. Highly leveraged counterparts are more vulnerable to default because relatively modest fluctuations in value can cause insolvency. Moreover, companies having low EBITDA to sales ratios, a low return on assets, a poor recent cash flow and/or returns are more vulnerable because earnings are autocorrelated. On the other hand, large firms are less likely to default as they have more diversified resources and an easier access to capital markets. Also country risk and industry classification are significant variables in our model.
Using several measures, the model proves to outperform alternative models. Out-of-sample, almost 88% of companies are classified correctly up to two notches of the real S&P rating. Besides its accuracy, the model proves easy to use and to apply. Quite a lot of models have been built with information that is available for only a limited number of counterparties, requiring broad applicability to be set as an important characteristic of our model.

While upgrading financial regulations and supervision in order to prevent future crises, many authorities are being confronted with the fact that risks taken in the process of financial intermediation are difficult to observe and assess from outside the financial institution. In the absence of tight regulations, this opaqueness exposes banks to runs and systemic risk. In order to reduce this lack of transparency, credit rating agencies (CRAs) provide information that can help various stakeholders to evaluate the credit risk of issues and issuers. Even though CRAs have been criticized a lot in the latest crisis, for many observers of financial markets, credit ratings continue to play an essential role.

The third chapter of this dissertation presents a joint examination of how different factors influence the assignment of S&P and Moody's long term bank ratings, using a unique data set covering different regions, bank sizes, and bank types. In doing so, we include new and accurate measures of bank and country specific variables. We find that S&P and Moody's use a different rating process. More specifically, when we analyse S&P bank ratings we find the same variables to be significant in a panel data setting from 2000 to 2009 and in the year 2009. This could indicate that S&P is rating through-the-cycle, which is further confirmed by the fact that no business cycle indicator seems to have a significant impact on the S&P bank ratings. Moody's seems to adjust its rating process throughout time. Different indicators are significant for the period 2000 to 2009 compared to the period 2009. Furthermore, we find that 3 out of 4 business cycle indicators are significant. After controlling for cyclical changes to business and financial risks, the slope of the yield curve and employment growth stay significant. Both of these findings could be interpreted as an indication of excess cyclicality.

Even though our focus is on the cyclical properties of ratings, we also provide evidence on trend behaviour of bank ratings. Our results indicate that previous findings of a secular tightening of corporate rating standards do not hold for banks. More specifically, after the inclusion of more complete measures of systematic changes to risk, we find no significant trend behaviour neither for Moody's nor for S&P. Finally, we checked our findings on a sample of banks that are rated by both rating agencies while controlling for potential sample selection bias. We find only limited evidence of mimicking behaviour between Moody's and S&P.

This paper provides clear evidence that Moody's and S&P do not have equivalent rating scales and rating processes. More specifically, it is shown that Moody's and S&P have different rating determinants, different sensitivity towards the business cycle and behave differently when rating banks that are rated by both of them.

We believe that the findings of this dissertation are highly relevant for various bank stakeholders and academics. As such, we hope that the outcome of our three chapters will be used in further discussions on the regulation of financial institutions, the role of ratings and rating agencies and finally, on how to reduce the tension field between theory, regulation and economic reality.

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