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Master Thesis

Thesis Master of Science

Banking regulation - A study of its effectiveness in reducing risk in European banks

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Start:	15.01.2019 09.00
Finish:	01.07.2019 12.00

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MSc in Finance

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Oslo, June 30, 2019

ABSTRACT

We gathered a dataset of 24 European banks from 10 different countries in order to test the effectiveness of European banking regulation through a fixed effects panel regression. Our results suggest that increased capital requirements, tier 1 capital ratio, and more supervisory power lead to higher bank risk. We also found that increased activity restrictions lead to lower risk, however, the coefficient estimate is not statistically significant. For the bank-specific and macro controls we find that return on assets and unemployment rate are the best predictors of bank risk. A higher return on assets will lead to lower risk while a higher unemployment rate leads to higher risk. We conclude that regulatory measures employed during this period were not effective in reducing risk.

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1. Introduction

The Global Financial Crisis (GFC) of 2008 and the subsequent Eurozone Crisis were both products of events that unravelled in the banking and lending sector in the years leading up to 2008. One reason why the risk levels rose so much was due to a fragmented banking system with varying regulation across countries. Following the crisis, the European Union (EU) moved towards centralizing their supervisory practices with the aim of reducing the divergence in the regulatory frameworks and establishing rules deciding adequate capital requirements (Goyal et al., 2013). The idea for our thesis is to investigate the relationship between regulation and risk in the European banking sector. Bank failures can have severe and long-lasting effects, especially if they are accompanied by a financial crisis. This has historically contributed to falling assets prices, rising unemployment, lower output, and higher government debt (Reinhart & Rogoff, 2009). The GFC was triggered by bank failures due to excessive risk-taking in the sector, which in turn was followed by a world-wide recession and costly government bailouts (Brandao-Marques et al., 2018). This provides us with a strong motivation to explore the main questions of our thesis topic: (1) are regulatory measures effective in reducing the riskiness of European banks, (2) does increasing strictness of regulation have a significant impact on risk, and (3) are there more important factors in determining risk than regulation?

One of the reasons why effective regulation is so important is because bank failures can have such adverse effects on the wider economy. This is due to how the modern banking system is designed. Banks are usually highly levered and hold few liquid assets on their balance sheet in a system called fractional reserve banking. The idea is that banks can create credit in the economy by accepting deposits and holding only a small fraction of those liabilities in reserves while the rest is loaned out to customers (Timberlake, 1984). In a critique of the fractional reserve banking system, Selgin (1988) outlines several inherent flaws that can lead to recurring crises. He claims that the system will (1) shift physical ownership of financial assets from owners to banks, (2) expand the money supply, and (3) thus exaggerate business cycles by providing stimulus to the demand for goods and services. The fractional reserve banking rules make the banking system more fragile due to high leverage, so when a collapse eventually happens, most of the losses fall on creditors and depositors, while shareholders simply lose their investment (Kaufman, 1996). Banks only have a small buffer to withstand losses because of this high leverage. Therefore, they are vulnerable to sudden increases in demand for cash which could lead to a bank run, fire sale of assets, contagion effects and other issues further discussed in section two.

The structure of this thesis is as follows. First, we discuss why banks are regulated, why they are important to the stability of the financial system, and why bank failures could prove so costly. This discussion will provide a background and motivation for why we are doing this research. Then we review existing literature on this topic to examine previous evidence for any relationship between regulation and risk. Afterwards, we will discuss the variables we chose to test the effectiveness of banking regulation and the hypotheses that we are examining. We then move on to present the model specification and analyse and test the robustness of the results. In the final section we will make a conclusion and answer the questions we have asked in the introduction.

2. Why banks are regulated

Regulation of banks in general is done to reduce the risk of failures, i.e., banks collapsing entirely or requiring a government- or investor-funded bailout. Keeping risk at an acceptable level is important because excessive risk-taking behaviour by banks leads to an increased chance of bank failures and government bailouts (Brandao-Marques et al., 2018). Therefore, the goal of banking regulation in Europe must be to avoid failures and ensure stability. The Single Supervisory Mechanism (SSM) constructed by the European Central Bank (ECB), which is the system of banking supervision in Europe, was created for this purpose. Its aims are to ensure the safety and soundness of the European banking system, increase financial integration and stability, and to ensure consistent supervision (ECB, 2018). A failure occurs, in theory, when the market value of a bank's assets falls below the value of its liabilities. The value of equity is then negative, and the bank is unable to pay off its debt in full in case of a liquidation (Kaufman, 1996).

Banks are highly levered, so taking on too much risk will make these outcomes more frequent and severe (Brandao-Marques et al., 2018). However, bankruptcies happen all the time in other sectors. Why do banks require such special attention by regulators, and why is a market-regulated solution supported by commercial and contractual law not enough? The answer lies in the role banks play in our economy, the unique characteristics of the banking sector, and the externalities caused by bank failures. In their book on financial regulation from 1998, Goodhart et al. outlines four main considerations explaining why bank regulation and supervision is necessary:

1. The pivotal position of banks in the financial system
2. The potential systemic danger resulting from a bank run
3. The nature of bank contracts
4. Adverse selection and moral hazard associated with the lender-of-last resort role and other safety net arrangements that apply to banks

As the world moves further away from cash as a means of payment, credit and debit cards, and other electronic payment solutions become increasingly important to the financial system. In the event of a bank failure, customers of the affected bank would experience problems accessing their funds immediately. If they can't use their cards to pay for goods and services, they would likely attempt to withdraw their savings and deposits which can start a bank run. Banks are also essential to the supply of credit and to the management of security clearances. For example, we can see by the following graph how the supply of domestic credit by banks changed when the GFC hit. First, we saw a decline from 2007 to 2008 of 2.13 % before a sharp increase of 8.62 % when governments started injecting capital into the sector to boost credit supply. The period in question is highlighted by a red box. Bank loans are the main source of financing for most private clients and businesses (Bernanke 1983). Therefore, a drop in the credit supply could have big effects on the wider economy.

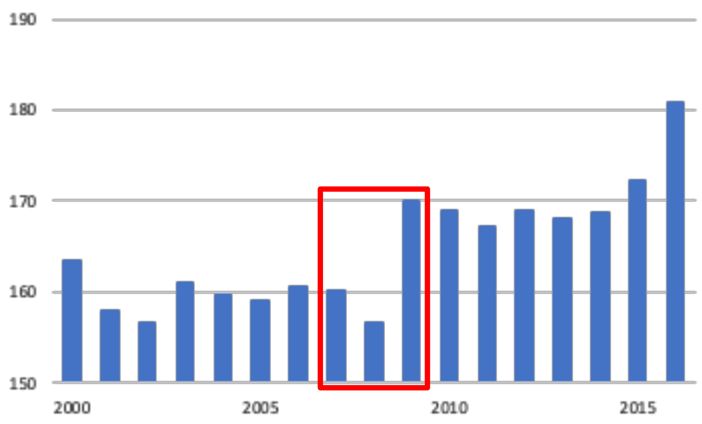

Figure 1. World domestic credit provided by the financial sector (% of GDP). Source: World Bank

The second consideration is regarding systemic effects from a bank run. A bank run occurs when many, or all, of the depositors at a bank fear that it will collapse and they rush to withdraw their funds (Diamond et al., 1983). These types of adverse event can spread rapidly throughout the economy due to customers fearing that their own bank can collapse as a result of the first bank collapsing. This is a product of the higher degree of interconnectedness that we see in the banking sector compared to other sectors (Cai et al., 2017). Third, the nature of bank contracts is different from other industries. Some of the advantages of using deposits instead of securities to store your money are economies of scale, smaller transaction costs, liquidity, and convenience (Merton, 1977). However, a fundamental problem faced by all banks is that they fund the acquisition of illiquid assets (loans) with liquid liabilities (deposits). Also, the average maturity of the loans they make are significantly higher than the average maturity of the deposits. Due to this liquidity and maturity mismatch, they are naturally vulnerable to large demands for quick cash, as will happen in the case of a run on the bank.

Governments have tried to prevent bank runs from happening by using deposit insurance. Under such a system, the government would act as a guarantor of the bank's ability to redeem deposits up to a certain value (Merton, 1977). EU rules currently state that deposits up to €100,000 are guaranteed (European Commission, 2019), while in the US the limit is $250,000 per depositor for all types of deposit accounts at each insured bank (Federal Deposit Insurance Corporation, 2018). The rationale behind such a scheme is that depositors don't have to monitor their bank to ensure the safety of their deposits, thus being able to engage in more productive activities. Also, if there are fears that a bank might collapse, most of the depositors will have their deposits guaranteed by the government, so there is no need to rush to the bank to make a withdrawal. This is a low-cost way of preventing bank runs since it only incurs a cost to the government if a bank collapse. It also protects smaller depositors and it promotes smaller bank's ability to raise capital through deposits (Demirgüç-Kunt and Kane, 2002). Although the policy is aimed at preventing bank runs, the scheme could lead to moral hazard and increased risk taking by banks. Since deposits under these limits are effectively risk free, the result is that banks offer lower deposits interest rates and grant riskier loans (Bao & Ni, 2017). The same article estimates that depositors will face a loss in their welfare "equivalent to at least a 3.27 % drop in deposit interest rates".

The fourth point brought forward by Goodhart et al. is regarding the risk of adverse selection and moral hazard occurring. This issue arises because banks have safety nets designed to limit the risk of them collapsing, one of them being the deposit insurance scheme that has become increasingly common throughout the world (Demirgüç-Kunt and Kane, 2002). The other is the fact that central banks act as a lender of last resort for banks that are deemed "too big to fail". Such banks are considered by the government to have a higher cost of failing than the money required to perform a bailout. The rationale behind such a concept is understandable, but it is easy to imagine situations where such a policy can have adverse effects on the incentives of those banks. There are arguments to be made that it encourages large banks to take on more risk (O'Hara and Shaw, 1990). This is because big banks can increase their upside potential by making riskier loans, while the downside remains unchanged since the government will bail them out in case of failure.

There are many valid reasons as to why the banking sector requires regulation that differ from other sectors. But apart from the structural characteristics of the sector, there are also potentially big effects from collapses in the banking sector that warrant a tighter regulatory regime. Bank failures can lead to sudden recessions, big drops in asset prices, protracted recoveries and big increases in government debt (Brandao-Marques et al., 2018). A recession can also be made worse by subsequent bank failures since they reduce the wealth of bank shareholders and shrink the supply of money (Bernanke, 1983). There is also a general perception that collapses in this sector can trigger further collapses and/or spread beyond the banking sector into the wider economy and other countries (Kaufman, 1996). Surviving rival banks will be adversely affected by failures, but these effects are smaller if the banks are well capitalised and regulated (Akhigbe & Madura, 2001). This is not something that most other industries share, and it is one of the main reasons why banks are so heavily regulated. E.g. a supermarket going bankrupt is unlikely to trigger more supermarkets going under. It would rather benefit the competitions since they can get a higher market share. In their paper from 2009, Reinhart and Rogoff found that the aftermath of severe financial crises often share three main characteristics:

1. Asset market collapses are deep and prolonged
2. Aftermath of banking crises is associated with profound declines in output and employment
3. The real value of government debt tends to explode

Not only are the effects severe in themselves, but the aftermath usually lasts a few years before the economy is back at the pre-crisis levels. We can see from the following graph how the world GDP growth rate fell from 4.2 % in 2007 to 1.8 % in 2008 and –1.74 % in 2009. The period in question is highlighted with a red box.

Figure 2. World GDP growth (annual %). Source: World Bank

For these reasons its clear why bank failures are best to be avoided. However, although the purpose of banking regulation is to reduce the risk of such events occurring, the question remains: is the current way of regulating banks effective in reducing risk? First, we must look at previous studies into this subject before we examine this question further.

3. Literature review

There is extensive literature examining the effectiveness of regulation on bank risk and other factors that might have an effect. In reviewing the existing research on this topic, we note two major observations. First, due to differences in regulatory frameworks across countries, there is no clear measure for the level of regulation that would allow for a clean comparison. However, several databases exist that can be used as a proxy. Second, the evidence for a relationship between capital, regulation and risk is mixed. Results vary with choice of risk proxy, regulation measures and sample. We review the literature on this topic to form a theoretical basis for our hypotheses and to point out how our analysis will differ from previous work in this area.

One of the most commonly considered factors in regulatory frameworks, and a cornerstone of the Basel accords, is bank capitalisation. Calem & Rob (1999) found evidence suggesting that the relationship between capital and risk is U-shaped. They concluded that moral hazard exacerbated the problem since undercapitalised banks tend to take on maximal risk, especially when near insolvency. As the level of capital increases towards the regulatory requirements, banks tend to reduce risk and it converges towards the industry normal. Finally, the overcapitalised banks may engage in riskier activities as they seek to compensate for smaller returns caused by a reduced amount of capital available for lending.

Baselga-Pascual et al. (2015) use a dynamic panel model to analyse factors that influence bank risk in the EU between 2000 and 2012. They use Z-scores and non-performing loan ratio[1] as proxies for risk and several bank-specific factors as explanatory variables. They also use indices of regulatory strictness as control variables and find that regulation reduces risk in their baseline model, but the evidence is mixed after running robustness checks. Furthermore, they conclude that reduced capitalisation has a significant effect on risk only in the crisis period. Another interesting finding relevant to our analysis is the relationship between bank size and risk. Although their baseline model showed an inverse relationship between the two, some of the robustness tests yielded a positive relationship.

Lee & Hsieh (2013) employ a dynamic panel data methodology to examine sources of risk in banking in 42 Asian countries between 1994 and 2008. They point to the ambiguous evidence for clear relationship between bank capital and risk in the previous research. They use a variance of the return on assets and variance of the return on equity as risk proxies. They find a reverse capital effect on risk for commercial banks, however, not all proxies for the level of regulation were negatively related to risk.

While the papers mentioned above mainly use the World Bank's index of regulation as a control variable, Klomp & Haan (2011) directly examined the impact of regulation on bank fragility. Using a sample of 200 banks from OECD countries between 2002 and 2004, they point to three main challenges tied to analysing the effectiveness of regulation. First, there is no universally accepted definition of banking risk. Most previous research focuses on balance sheet measures such as Z-scores or NPLs. This provides further motivation to focus more on market measures in our thesis and see how our results differ from previous findings. Second, they point to many different dimensions of banking regulation. They use the data from Barth et al. (2004, 2008) to construct seven measures of banking regulation. Finally, they assume that the relationship between regulation, supervision and risk might not be homogenous. Their findings are mixed, and they conclude that supervisory control and capital regulations have significant effects on capital and asset risk, while activity restrictions have a significant effect on liquidity and market risk. Those three measures are especially important to our analysis as we focus on them in our

[1] NPLs as a fraction of total loans

model. Another important conclusion coming from their work is that effect of regulation depends on ownership structure and the size of the bank. We control for the former by focusing only on listed banks and for the latter by including a control variable for size in the model. However, they point out that their results are not uniform. Regulation has a minimal effect on low-risk banks, while the opposite holds for those with riskier assets.

Measuring differences in level of regulation between countries is a challenging task. Pasiouras et al. (2009) look at the relationship between regulation, competition and risk in banks in transition economies in the period 1998-2005. The regulatory measures considered in their study are capital requirements, restrictions on activities and official supervisory power. They choose the database on banking regulation complied by Barth et al. to obtain measures of those three dimensions. They focus, however, solely on countries transitioning from central to market economies, while all bank in our sample are from developed countries. Measures of risk also differ. Similarly, to other literature on this topic, they conclude no clear relationship between regulation and risk. They find that capital requirements and supervisory power have an impact on credit risk, and they reduce non-performing loans. However, that relationship is less pronounced with banks with a moderate market power and is reversed for banks with high market power. They point to the possibility of country-level institutional characteristics affecting the bank risk. In our research we aim to minimize that issue by focusing on EU banks where many regulatory and fiscal policies are aligned across countries.

Schuermann (2013) examines how much capital and liquidity a bank needs to support its risk-taking activities. During the GFC, many of the failed banks were adequately capitalized. This clearly showed that regulatory capital was not a credible indicator of a bank’s resilience to shocks. Bank balance sheets are often opaque and prone to easy swapping of high risk for low risk assets. Moreover, even the high-quality assets can suffer from reduced liquidity. This provides rationale for other forms of regulation, beyond simply monitoring capital ratios.

4. Data

To measure the strictness of regulation we use the World Bank Survey on Regulation compiled by Barth et al (1999, 2003, 2007, 2011). Our sample covers the period 2000-2012 and it consists of 24 listed banks from 10 European countries. We do not include banks that purely engage in investment banking as the characteristics of those institutions may significantly affect the risk-taking profile (Baslega-Pasucal et al., 2015). The balance sheet data needed for the regression inputs was collected from Bloomberg and complimented by annual statements of respective banks, should there be any data missing. To standardise the currency for all banks in the sample, we converted some data to Euro. The data for macroeconomic variables was sourced from the World Bank.

The credit default swap data series were obtained from Datastream and came from two providers – CMA and Thomson Reuters. The CMA data was discontinued from 2008, therefore the data series of each banks was compiled by combining quotes from the two sources. After obtaining monthly series, an annual average was compiled. All CDS were Euro-denominated. CDS quotes are available from 2004 onwards, which results in shorter sample compared to the one that uses Merton distance to default as a risk proxy.

5. Variables

5.1 Dependent variables

Risk is what is referred to as a latent variable in statistics. This means that it is not something that we can observe directly, like we can read profits from the income statement, but rather must be inferred from other measures. Risk, as discussed in our thesis, will refer to the probability of a bank failing entirely or requiring a government- or investor-funded bailout. We have identified credit default swap spreads and Merton's distance to default model as viable proxies to measure individual bank risk. The CDS spreads gives us the option to use the market's sentiment of perceived risk of a bank while the Merton model is a more theoretical approach combining balance sheet and market data.

5.1.1 Credit default swaps

A CDS is a type of credit derivative, which means that the payoff from this contract is contingent on the creditworthiness of the issuer of the underlying credit security (Longstaff et al., 2005). This type of security can be used for hedging, speculation, or arbitrage activities. Due to this flexibility, CDSs are the largest class of credit derivatives. Any CDS contract will have three parties: (1) the party buying the contract, (2) the party selling the contract, and (3) the party issuing the bond underlying the contract. The buyer will pay the seller a premium, usually per quarter, for protection against different credit events occurring in the period specified in the contract. Credit events for a bank could be (1) bankruptcy, (2) failure to pay interest and/or principal when due, (3) obligation default or acceleration, or (4) restructuring (Blanco et al., 2005).

In the case of such a credit event, the seller pays the buyer the equivalent of the difference between the par value and the market value after default. If nothing happens in the contract period, then the seller simply collects the premiums and pays nothing. Buying a CDS is therefore a bet on a company's ability to repay its debt and the price should therefore reflect the probability of default. Investors use this to reduce their exposure to defaults in their bond portfolio. Through a CDS contract, they can transfer their credit risk from the bond issuer to the seller of the contract by trading a derivative instead of selling the bond. CDS spreads are an upper limit on the price of credit and they are therefore a useful measurement of credit risk (Blanco et al., 2005).

CDS prices also lead the stock market and credit ratings in the price discovery process (Acharya & Johnson, 2007; Hull et al., 2004). They are also market traded securities that are highly standardised, which makes them much more liquid than debt issue prices since bond issues are more specialised and less traded (Hart & Zingales, 2011). The same article also points out that equity prices are less suited as a proxy for default risk since stock prices are insensitive on the downside because of limited liability and sensitive on the upside. Most of the previous research on this subject have used other risk measures than CDS spreads. We therefore think it would be interesting to use this as one of our dependent variables.

5.1.2 Merton model for structural credit risk

Black and Scholes developed a theoretical valuation formula for options and showed how different corporate liabilities such as stocks, bonds and warrants can be described as a mix of different options and thus valued using their framework (Black & Scholes, 1973). They also showed how the now famous Black and Scholes formula could be used to derive appropriate discount rates for corporate bonds due to the probability of default. Merton then developed a structural credit risk model based off their paper that he called "a theory of the risk structure of interest rates" (Merton, 1974). The basic theory of the model is that the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt. Since the Merton model can be used to determine the value of a corporate debt issue, it should also be able to determine the probability of default since that is a part of the pricing of debt. Therefore, the KMW corporation developed a particular application of the model which they named the Merton distance-to-default model (MDD model) (Bharath & Shumway, 2008). The MDD model makes two critical assumptions:

1. Total market value of a firm follows a geometric Brownian motion given by:

   $$dV = \mu V dt + \sigma_V V dW$$

   Where V is total value of firm, μ is the expected continuously compounded return on V, σ_V is volatility of firm value, and dW is a standard Wiener process
2. The firm has issued just one discount bond maturing in T periods

Under these assumptions, the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt and a time-to-maturity of T. Moreover, the value of equity as a function of the total value of the firm can be described by the Black and Scholes formula. By put-call parity, the value of the firm's debt is equal to the value of a risk-free discount bond minus the value of a put option written on the firm, again with a strike price equal to the face value of debt and a time-to-maturity of T. Default will then happen if the value of the firm's assets falls below the value of debt, thus making the value of equity negative rendering the "put option" worthless. The MDD model makes use of two important equations:

1. The first is the Black-Scholes-Merton equation, expressing the value of a firm's equity as a function of the value of the firm:

$$E = VN(d_1) - e^{-rT}FN(d_2)$$

   Where E is the market value of firm equity, F is face value of firm's debt, r is the instantaneous risk-free rate, and N (…) is the cumulative standard normal distribution function. d_1 and d_2 is given by:

$$d_1 = \frac{\ln\left(\frac{V}{F}\right) + (r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}$$

$$d_2 = d_1 - \sigma_V\sqrt{T}$$

2. The second related the volatility of the firm's value to the volatility of its equity. Under Merton's assumptions the value of equity is a function of the value of the firm and time, so we can use Ito's lemma and $\frac{\delta E}{\delta V} = N(d_1)$ that:

$$\sigma_E = \left(\frac{V}{E}\right)N(d_1)\sigma_V$$

In most applications, the Black-Scholes-Merton model describes the unobserved value of an options as a function of variables that are easily observable. However, in the MDD model, the value of the options is observed as the total value of the firm's equity, while the value of the assets is not directly observable. Thus, while

V must be inferred, E is easy to observe in the marketplace by multiplying the firm's outstanding shares with the stock price. Similarly, volatility of equity can be estimated but volatility of the assets must be inferred. There is a circularity issue since value of equity is a function of the value of assets and vice versa. We must therefore apply an iterative procedure in MATLAB to solve this system of nonlinear equations to translate the value and volatility of a firm's equity into an estimated distance to default, given by d_1, and an implied probability of default, given by:

$$\pi_{Merton} = N(-Distance\ to\ Default)$$

If the model holds, then π_{Merton}, and distance to default will give an indication of the likelihood of a firm defaulting. Therefore, it can be used as a proxy measuring risk, i.e., an LHS variable in our regression together with the CDS spreads. We chose to use distance to default instead of probability of default since it is more suitable for modelling purposes. The problem with probability of default is that it cannot take on values below 0, so the sample is biased which can be shown in Figure 3. By using distance to default instead, we have a sample that is unbiased which is illustrated in Figure 4. Distance to default measures the amount of standard deviations between expected asset value at time T and the computed liability threshold.

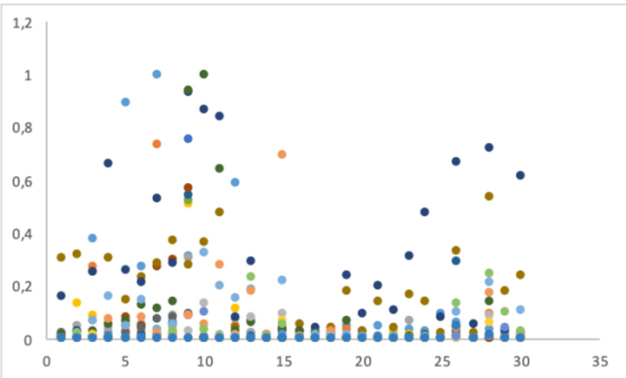

Figure 3. Scatter plot of estimated probability of default

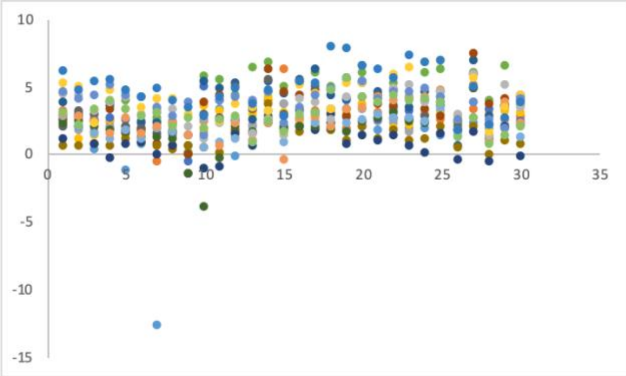

Figure 4. Scatter plot of estimated distance to default

5.2 Regulatory variables

Due to the purpose and rigorousness of current regulation, we expect to find evidence supporting our current hypothesis, i.e., that regulation reduces risk in the European banking sector. However, measuring regulation directly is impossible, so we must use a quantifiable index that we can include in the regression. With respect to measuring strictness of regulation we are using data from Barth et al.'s (2011) bank regulatory database published by the World Bank. This database was created to "measure the intensity and breadth of regulation in the banking sector and at the country level". Four surveys were conducted in the period 1999-2011 and cover over 180 countries for which the authors collected responses to hundreds of questions covering topics such as capital policies, power of government regulators, role of private monitoring and many others. The results were then translated into different indices where a higher number corresponds to stricter regulations.

We choose to focus on three specific sub-sections of the survey for our model, namely the ones concerning capital stringency, level of official bank supervisory power, and an index of activity restrictions. From the sections available in the survey, these are ones that are most closely tied to the main question of this thesis. The choice of the regulatory variables is similar to the methodology of Brandao-Marques et al (2018) who use the same indices to control for country-specific regulations when examining determinants of risk on a sample of 321 banks globally. We assume that the strictness of regulation stays constant in-between the surveys. This approach is in line with paper by Baselga-Pascual et al. (2015) where they employ the index to measure the strictness of regulation in a large sample of Eurozone banks between 2001 and 2012. We will also use the Tier 1 capital ratio of banks as a regulatory variable in our regression.

5.2.1 Index of capital requirements (CR)

The capital stringency index is constructed by looking measures of capital stringency in a country. Overall capital stringency indicates whether risk elements and value losses are considered while calculating the regulatory capital. It is based on the following questions[2]:

Table 1. Components of the capital regulation index

1.	Is the minimum capital–asset ratio requirement risk weighted in line with the Basel guidelines?
2.	Does the minimum ratio vary as a function of credit risk?
3.	Does the minimum ratio vary as a function of market risk?
4.	Are market values of loan losses not realized in accounting books deducted from capital?
5.	Are unrealized losses in securities portfolios deducted from capital?
6.	Are unrealized foreign exchange losses deducted from capital?
7.	What fraction of revaluation gains is allowed as part of capital?
8.	Are the sources of funds to be used as capital verified by the regulatory or supervisory authorities?
9.	Can the initial disbursement or subsequent injections of capital be performed with assets other than cash or government securities?
10.	Can the initial disbursement of capital be performed with borrowed funds?

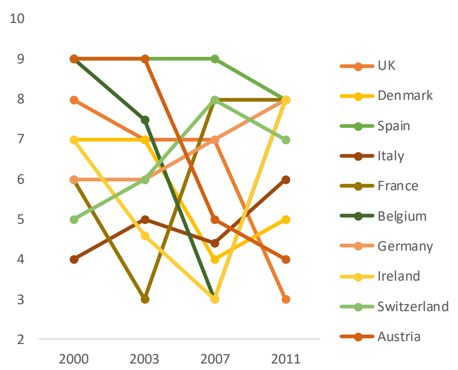

Figure 5. Index of capital regulation for different countries

[2] For each question to which the answer is 'yes', the value of 1 is assigned and 0 if the answer is 'no'. The final value of the index falls between 0 and 10 and is obtained by summing up all answers to the questions.

On average, the index of capital regulation decreases following the early 2000s recession and increases following the GFC. While the value of the index rose for some countries after the crisis, the capital regulations were substantially relaxed in others, such as the United Kingdom an Austria (Barth et al 2012). This results in highest variance among all 3 indices and only small average increase post-crisis.

Hypothesis: Stricter capital regulation will decrease risk.

5.2.2 Index of supervisory power (SP)

This purpose of this index is to measure the extent to which authorities have power to obtain information about financial entities operating in their jurisdiction and the degree to which they can intervene should an action be required. The index is constructed by collecting answers to the following questions[3]:

Table 2. Components of the supervisory power index

1.	Does the supervisory agency have the right to meet with external auditors about banks?
2.	Are auditors required to communicate directly to the supervisory agency about elicit activities, fraud, or insider abuse?
3.	Can supervisors take legal action against external auditors for negligence?
4.	Can the supervisory authority force a bank to change its internal organizational structure?
5.	Are off-balance sheet items disclosed to supervisors?
6.	Can the supervisory agency order the bank's directors or management to constitute provisions to cover actual or potential losses?
7.	Can the supervisory agency suspend the directors' decision to distribute (a) dividends, (b) bonuses, and (c) management fees?
8.	Can the supervisory agency supersede the rights of bank shareholders and declare a bank insolvent?
9.	Can the supervisory agency suspend some or all ownership rights?
10.	Can the supervisory agency (a) supersede shareholder rights, (b) remove and replace management, and (c) remove and replace directors?

[3] The index takes values from 0 to 14, where a greater value indicates a greater degree of supervisory power. Each question has a value of 1 if the answer is "yes" and 0 if the answer is "no". Questions 7 and 8 take values from 1 to 3.

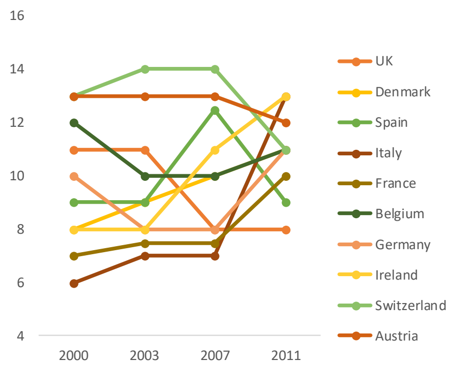

Figure 6. Index of supervisory power

In the run-up to the GFC, supervisory power remained broadly unchanged although it slightly increased on average following the GFC. The variance of values noticeably decreased post-crisis. This could indicate a convergence of rules and more integrated supervisory approach in the post-crisis years.

Hypothesis: More supervisory power will decrease risk.

5.2.3 Index of activity restrictions (AR)

Finally, the index of activity restrictions measures how restrictive the regulators are in controlling activities that go beyond the traditional role of banks as providers of credit. Those activities are broken down into three categories[4]:

Table 3. Components of the activity restrictions index

1.	Securities activities
2.	Insurance activities
3.	Real estate activities

[4] Each category takes a value from 0 to 4, making the total score of the index between 0 and 12. Higher value indicates higher restrictiveness. For specific questions asked in each category please see appendix B.

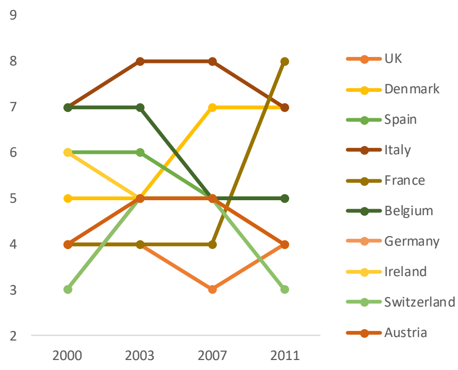

Figure 7. Index of activity restrictions

Beck et al. (2006) find that there is a great variability across countries in terms of what activities banks can engage in. From the graph above, we can see that it is difficult to detect any obvious trends. This might be due to changing definitions and notions of what constitutes traditional activities, making the three categories difficult to separate. However, our sample consists of mostly Eurozone banks where the divergence of regulatory definitions is limited. Therefore, classification of activities does not vary substantially (ECB, 2018). The average value of the index drops in 2007 although it does not change significantly throughout the sample period.

Hypothesis: More activity restrictions will reduce risk.

5.2.4 Tier one capital ratio

Capital ratios are one of the most important tools used by regulators. Its main purpose is to absorb unexpected losses that could arise in periods of market turbulence. The Basel Committee defines tier 1 capital ratio as follows:

$$Tier\ 1\ Capital\ Ratio = \frac{Tier\ 1\ Capital^{5}}{Total\ Risk\ Weighted\ Assets^{6}}$$

While the Basel agreement provides general guidelines and minimum thresholds, country and bank-specific targets may be significantly higher. Assets used to build capital buffers are also a subject to country-specific adjustments (Blundell-

[5] Tier 1 Capital = Value of common stock and retained earnings
[6] Sum of assets weighted according to risk profile

Wignall et al., 2014). We therefore use Tier 1 capital ratio as an explanatory variable to test its significance in explaining bank risk. Increased capital ratios have been found to reduce the non-performing loans (Gaganis et al., 2006). We lag the tier 1 ratio, to see how the end-of-year value impacts the average risk for the following year. This leads us to the following hypothesis:

Hypothesis: Banks with higher Tier 1 capital ratios are less risky.

5.3 Control variables

According to Baselga-Pascual et al. (2015), we can separate the risk of an individual bank into two main components:

1. Factors that are specific to each bank. These are largely decided by managerial decisions and corporate culture. This could be asset structure, capitalisation, diversification, size etc. Managers can make changes to these factors and thus influence the risk of their bank. E.g., become better capitalised to reduce risk. We have chosen asset size and return on assets to control for the effects of these factors.
2. Systemic factors. These factors are the same for all banks. Can be GDP growth, interest rates, inflation rates, unemployment etc. A change in any of these factors will affect the risk profile of all banks that operate in a given area. E.g., if unemployment increases in Norway, then all banks operating in the country will be adversely affected. We have chosen GDP growth rate, change in inflation, and unemployment rate to control for the effects of these factors.

5.3.1 Size

There is widespread literature on the relationship between size and bank risk, especially after the GFC where we saw many banks being assisted with capital injections from the government. The main theory is that larger banks are riskier than smaller ones due to the moral hazard problem brought forward by past bailouts (Uhde & Heimeshoff, 2009; De Jonghe, 2010). This is because they observe that large banks have been bailed out earlier, so they assume that they will do the same again. Evidence has been found in support of this hypothesis, but only up to a certain size threshold (Louzis et al., 2012). Other papers suggest the opposite (Boyd & Prescott, 1986; Salas & Saurina, 2002). They suggest that a bigger size could allow for more diversification opportunities. Therefore, a less concentrated asset composition could lead to lower risk. Salas & Saurina found evidence in support of this hypothesis in their paper from 2002. Since there are conflicting views as to how size affects bank risk, we propose two hypotheses:

Hypothesis (a): Bigger size of assets leads to lower risk.
Hypothesis (b): Bigger size of assets leads to higher risk.

We are using the natural logarithm assets in €m because of the big range in values in the sample. This is necessary to eliminate the possibility of outliers affecting the regression results. We can clearly see how the scatter plot changes and become more suited for modelling when we change to log size in Figure 8 and 9.

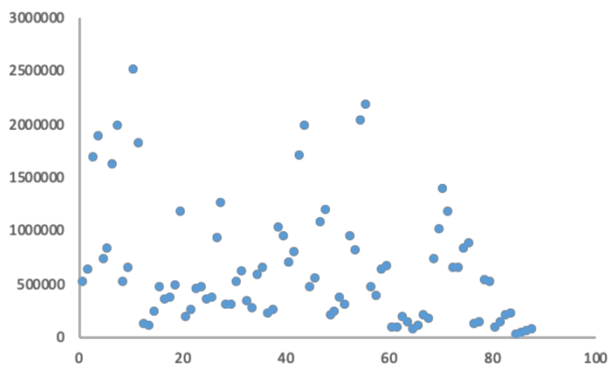

Figure 8. Assets size in €m

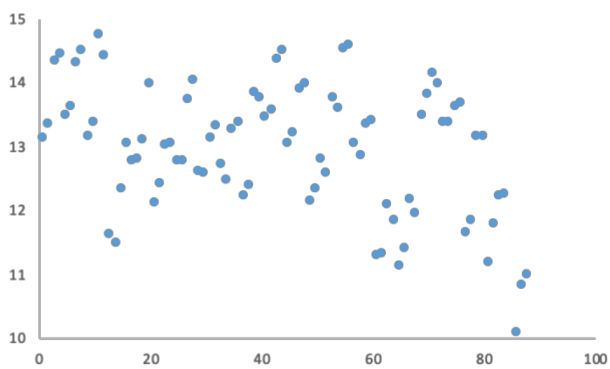

Figure 9. Log (asset size)

5.3.2 Profitability

Poghosyan & Čihak used a data set on bank distress to examine which factors that explain risk in EU banks in a paper published in 2011. They found that profitability and risk were negatively related and that the coefficient for profitability was statistically significant in all variations of their regression analysis. Louzis et al. argue through two different hypotheses how past performance might affect future risk. The first, named “Bad management II”, say that past performance is negatively related to risk due to good management. The second, named “Pro-cyclical credit policy”, say that past performance is positively related to future risk since it implies that the bank has taken on excess risk to boost short-term profitability at the expense of long-term losses. They found evidence in support of the Bad management II hypothesis, but no evidence for the Pro-cyclical credit policy hypothesis. Therefore, their results suggest that performance and bank risk are negatively correlated. We also suspect that the effect of ROA on risk is going to be stronger when crisis years are removed from the regression since the systematic risk component will be smaller. Thus, we propose the following hypotheses:

Hypothesis (a): A bank with higher return on assets will have a lower risk.
Hypothesis (b): The effect of ROA on risk will be stronger when crisis years are removed

5.3.3 Economic growth

There is a general perception that the banking sector is pro-cyclical and that better economic times are associated with lower risk and fewer defaults. There are many studies that examine this effect and find evidence in support of this hypothesis (Poghosyan & Čihak 2011; Baselga-Pascual et al., 2015). Studies have also found evidence suggesting that a higher real GDP growth rate is associated with lower risk (Bofondi & Ropele, 2011). However, most of these studies use other dependent variables such as NPL ratios or bank distress events. Since we use different dependable variables, we would like to see if we can obtain the same results with other variables being used to measure risk. Therefore, we propose the following hypothesis:

Hypothesis: A higher GDP growth rate leads to lower bank risk.

5.3.4 Inflation

A stable inflation rate is usually associated with a stable and thriving economy. This is one of the reasons why inflation targeting has become the main way of managing a country's monetary policy instead of exchange rate targeting (Bernake & Mishkin, 1997). We also know that increasing rates of inflation translates into higher nominal interest rates, which causes more difficulties in managing debt due to higher interest payments. On the other hand, higher inflation causes the real value of debt to erode over time. Evidence has been found in a study of Italian banks suggesting that higher rates of inflation is associated with a higher degree of bad loans on the balance sheet (Bofondi & Ropele, 2011). Other papers argue that an increasing inflation rate is accompanied by bank distress events (Männasoo & Mayes, 2009). Due to these results, we propose the following hypothesis:

Hypothesis: A higher rate of inflation is associated with a higher degree of risk

5.3.5 Unemployment

A higher unemployment rate is usually associated with a downturn in the wider economy. As we discussed previously, the banking industry is pro-cyclical, so we would expect bank risk to increase when there is a downturn. There have been studies using unemployment as an explanatory variable in deciding bank risk. Bofondi & Ropele (2011) found that the number of bad loans on a bank's balance sheet correlated positively with the unemployment rate when studying Italian banks between 1990 and 2010. Another study found evidence suggesting that an increasing rate of inflation causes a higher NPL ratio (Louzis et al., 2012). Therefore, we suggest the following hypothesis:

Hypothesis: Higher rates of unemployment are associated with higher levels of risk.

5.4 Summary statistics

Table 4. Summary statistics

	Dependent Variables		Independent Variables								
	Risk proxies		Regulatory variables				Bank-specific variables		Macro variables		
Year	Merton_dd	CDS	Tier 1	SP	AR	CR	Logsize	ROA	Inflation	GDP	Unemployment
2000	**1.07**	**-**	**7.95**	**9.73**	**4.73**	**7.00**	**12.45**	**0.80**	**2.23**	**4.36**	**7.28**
	(3.28)		(1.78)	(2.19)	(1.39)	(1.63)	(0.99)	(0.35)	(1.34)	(1.75)	(3.58)
2001	**2.12**	**-**	**7.85**	**9.73**	**4.73**	**7.00**	**12.54**	**0.52**	**2.17**	**2.52**	**6.51**
	(0.93)		(1.52)	(2.19)	(1.39)	(1.63)	(0.99)	(0.29)	(0.99)	(1.32)	(2.71)
2002	**2.09**	**-**	**7.92**	**9.73**	**4.73**	**7.00**	**12.53**	**0.48**	**2.07**	**1.88**	**6.85**
	(0.65)		(1.28)	(2.19)	(1.39)	(1.63)	(0.92)	(0.38)	(1.12)	(1.69)	(2.7)
2003	**2.36**	**-**	**8.04**	**9.57**	**5.09**	**6.26**	**12.56**	**0.57**	**2.01**	**1.63**	**7.13**
	(1.01)		(1.09)	(2.17)	(1.23)	(1.9)	(0.95)	(0.39)	(1)	(1.55)	(2.63)
2004	**2.87**	**15.23**	**8.52**	**9.57**	**5.09**	**6.26**	**12.69**	**0.68**	**1.92**	**2.81**	**7.11**
	(1.21)	(3.55)	(1.39)	(2.17)	(1.23)	(1.9)	(0.99)	(0.28)	(0.68)	(1.44)	(2.6)
2005	**4.18**	**12.00**	**8.29**	**9.57**	**5.09**	**6.26**	**12.98**	**0.72**	**2.16**	**2.72**	**6.88**
	(1.61)	(3.1)	(1.46)	(2.17)	(1.23)	(1.9)	(0.97)	(0.29)	(0.58)	(1.36)	(2.41)
2006	**3.40**	**9.02**	**8.13**	**9.57**	**5.09**	**6.26**	**13.18**	**0.74**	**2.24**	**3.30**	**6.65**
	(1.78)	(2.24)	(1.45)	(2.17)	(1.23)	(1.9)	(0.93)	(0.3)	(0.66)	(0.97)	(2.14)
2007	**2.95**	**18.37**	**8.46**	**9.45**	**5.32**	**6.49**	**13.31**	**0.67**	**2.10**	**3.08**	**6.20**
	(1.67)	(7.63)	(1.74)	(2.34)	(1.51)	(2.02)	(0.97)	(0.39)	(0.6)	(1.12)	(1.86)
2008	**3.03**	**88.52**	**7.87**	**9.45**	**5.32**	**6.49**	**13.38**	**0.12**	**3.38**	**-0.04**	**6.65**
	(1.33)	(25.76)	(1.19)	(2.34)	(1.51)	(2.02)	(0.98)	(0.6)	(0.53)	(1.67)	(2.4)
2009	**0.87**	**140.10**	**8.78**	**9.45**	**5.32**	**6.49**	**13.33**	**0.14**	**0.44**	**-4.01**	**9.17**
	(0.6)	(68.4)	(1.53)	(2.34)	(1.51)	(2.02)	(0.93)	(0.54)	(1.17)	(1.12)	(4.13)
2010	**0.58**	**131.33**	**11.05**	**9.45**	**5.32**	**6.49**	**13.36**	**0.04**	**1.69**	**1.89**	**9.74**
	(1.15)	(44.64)	(2.41)	(2.34)	(1.51)	(2.02)	(0.96)	(1.46)	(1.35)	(1.02)	(4.88)
2011	**1.40**	**310.97**	**11.59**	**10.14**	**5.15**	**6.27**	**13.39**	**0.00**	**2.83**	**1.70**	**9.84**
	(1.7)	(62.2)	(2.96)	(1.58)	(1.69)	(2.12)	(0.98)	(0.6)	(1.28)	(1.43)	(5.58)
2012	**1.71**	**351.39**	**12.37**	**10.14**	**5.15**	**6.27**	**13.37**	**-0.05**	**2.22**	**-0.06**	**10.57**
	(0.88)	(84.54)	(2.01)	(1.58)	(1.69)	(2.12)	(0.99)	(0.71)	(1.02)	(1.63)	(6.59)

This table reports means and standard deviation in parentheses across all banks for all years in our sample. The sample spans 24 banks and totals 282 observations with MDD as the risk proxy, and 193 observations with CDS. Numbers for MDD represent standard deviations away from default, for CDS it is the spread quoted in basis points, Tier one is a ratio of total capital, SP is the supervisory power index taking values from 1 to 14, AR is the activity restrictions index taking values from 1 to 12 and CR is the capital restriction index taking values from 1 to 10. Logsize are the total assets in the logarithmic form, ROA is the net income divided by average total assets given in percentage. All macro variables are the percentage change on the previous year.

Table 4 presents summary statistics for our data. Following the early 2000's recession the distance to default and CDS spreads were gradually improving, signalling the market's confidence in the health of the banking sector. During the sub-prime crisis of 2008, the distance to default drops sharply and CDS spreads spike up. Moreover, we see a second, more severe, increase in average risk of the banks as measured by CDS spreads in 2011. This is caused by the sovereign debt crisis in the Euro area. The standard deviation of risk proxies also increased in that period. A potential reason could be that the riskiest banks were concentrated in a few countries, namely Italy, Spain and Ireland. Tier 1 ratio increases significantly on average following the GFC, reflecting stricter capital rules and capital injections from governments.

6. Methodology

We will use a panel regression analysis to measure the effectiveness of banking regulation in Europe. Saurina et al. (2002) use panel regression to test the degree to which capital buffers contribute to stability of Spanish banks. He points to the risk of omitted variables in assessing the likelihood of bank failure. We therefore consider the existence of other macroeconomic factors and include variables that might significantly affect the risk of a bank except for regulation. Baldagi (2001) points to benefits of panel model compared to a simple cross-sectional regression. Panel analysis considers all cross-section units as heterogeneous which helps to get an unbiased estimation. We are running the following panel regression:

$$\begin{aligned} Y_{it} = \beta_0 + \beta_1 Tier1_{i,t} + \beta_2 SP_{i,t} + \beta_3 AR_{it} + \beta_4 CR_{i,t} + \beta_5 Logsize_{i,t} + \beta_6 ROA_{i,t} \\ + \beta_7 Inflation_{i,t} + \beta_8 GDP_{i,t} + \beta_9 Unemployment_{i,t} + \beta_{10} Z_i + u_{i,t} \end{aligned}$$

Z_i are the unobserved time-invariant heterogeneities across banks. Y is the CDS spread or Merton distance to default. By letting $\alpha_i = \beta_0 + \beta_{10} Z_i$ (i = 1, …, 24) the model becomes:

$$\begin{aligned} Y_{it} = \alpha_i + \beta_1 Tier1_{i,t} + \beta_2 SP_{i,t} + \beta_3 AR_{i,t} + \beta_4 CR_{i,t} + \beta_5 Logsize_{i,t} + \beta_6 ROA_{i,t} \\ + \beta_7 Inflation_{i,t} + \beta_8 GDP_{i,t} + \beta_9 Unemployment_{i,t} + u_{i,t} \end{aligned}$$

Where α_i's are bank-specific intercepts that capture heterogeneities across entities. By containing information on intertemporal dynamics and individuality of each bank we can control the effects of missing and unobserved variables (Hsiao, 2007). Such variables could be for example corporate governance, managerial skills, and human capital. Fixed effects estimation removes unobserved heterogeneity from the regression which allows us to disregard the differences in bank-specific characteristics of regulation ($\alpha_i's$) that do not change through time. We therefore estimate the following model:

$$Y_{it} = \beta_1 Tier1_{i,t} + \beta_2 SP_{i,t} + \beta_3 AR_{i,t} + \beta_4 CR_{i,t} + \beta_5 Logsize_{i,t} + \beta_6 ROA_{i,t} + \beta_7 Inflation_{i,t} + \beta_8 GDP_{i,t} + \beta_9 Unemployment_{i,t} + u_{i,t}$$

Following the methodology by Kleiber and Zeleis (2008) we perform several tests of our model to check the robustness of results, which includes a pooled cross-section OLS analysis. The robustness of results is presented in the section after the discussion of results.

7. Discussion of results

This section is divided into four parts. First, we discuss the general results from the two regressions where MDD is dependent variable and repeat the same exercise for CDS. Then we will discuss each variable in more detail and look at whether the results are in line with our hypothesis. We will also run various robustness checks to test our models and make some suggestions for future research into this topic.

7.1 Discussion of results

We start off by looking at the model where MDD is the dependent variable. Here, a higher value of the dependent variable, i.e., a bigger distance to default, means lower risk. We test the model on two different time periods: 2000 – 2012 and the same period but removing the years 2009 and 2010 from the sample due to the euro crisis to see if there is any difference in the results. In the standard model we have an R-squared of 27.4 % with 282 observations and in the ex-crisis model the R-squared drops to 22.3 % with 238 observations. This suggests that the explanatory power of the model drops slightly when we remove the effects of the euro crisis.

Table 5. Panel regression output with MDD model as dependent variable

	2000 - 2012			2000 - 2012 ex crisis		
	Adj. R-squared = 0.27377, n = 22, N = 282			Adj. R-squared = 0.2228, n = 22, N = 238		
Coefficients	**Estimate**	**p-value**	**Significance**	**Estimate**	**p-value**	**Significance**
Tier 1	-0.0696	0.1905		0.0128	0.8270	
Capital requirements	-0.1642	0.0079	**	-0.1302	0.0584	+
Supervisory power	0.0605	0.3622		-0.0320	0.6563	
Activity restrictions	0.0511	0.6090		0.0777	0.4833	
Logsize	0.7316	0.0025	**	1.0592	2.77E-05	***
ROA	0.5780	0.0003	***	0.8755	0.0003	***
Inflation	0.0823	0.3752		-0.1342	0.3130	
GDP	0.0481	0.2854		-0.0932	0.1338	
Unemployment	-0.2109	1.36E-06	***	-0.2498	2.44E-07	***

p-value 0.10 – 0.05: +, 0.05 – 0.01: *, 0.01 – 0.001: **, < 0.001: ***

First, in the regulatory variables, we notice that the coefficient for Tier 1 is insignificant in both regressions. The coefficient also changes sign from negative to positive in the ex-crisis model. This is interesting considering that the MDD model uses value of equity as a significant input representing “put” value. The only regulatory index to achieve significant results is Capital requirements. The effect is negative and statistically significant at the 1 % and 10 % for the standard and ex-crisis model respectively. Activity restrictions decrease risk but is insignificant in both regressions. The evidence for Supervisory power is mixed an statistically insignificant.

The bank-specific controls, Logsize and ROA, are positive and significant across both regressions. We see that the effect of Logsize increases approximately 48 % and ROA by 51 % when the crisis year are removed. This suggests that these variables have a stronger effect on bank risk in less turbulent times. Although it is hard to make a definitive conclusion as to why the changes are so big, we hypothesise that it is due to the large systemic component present in the data for the crisis years. During such times, individual bank characteristics might be less important since the entire system is fragile and the banking sector being prone to contagion effects.

Inflation and GDP both change sign from positive to negative when the crisis years are removed. But it is hard to draw any conclusions since the results are insignificant across both regressions. Unemployment is negative and statistically significant at the 0.1 % level in both versions.

Now we run the same model again but use CDS as dependent variable to see if the results change in any significant way. CDS data was not readily available for most of the banks in our sample before 2004. Therefore, the sample is shorter in this version. The same years are removed in the ex-crisis version of the regression as we did when MDD was the dependent variable. As opposed to the MDD version, we see that R-squared increases from 57.8 % to 77.4 % when the crisis year are removed. This result suggests that our setup is better at explaining variations in CDS spreads than the estimated distance to default.

Table 6. Panel regression output with CDS spreads as dependent variable

	2004 - 2012			2004- 2012 ex crisis		
	Adj. R-squared = 0.57804, n = 22, N = 193			Adj. R-squared = 0.77379, n = 22, N = 149		
Coefficients	**Estimate**	**p-value**	**Significance**	**Estimate**	**p-value**	**Significance**
Tier 1	18.60	0.0002	***	11.88	0.0127	*
Capital requirements	33.89	1.23E-07	***	17.73	0.0055	**
Supervisory power	19.52	0.0043	**	18.44	0.0041	**
Activity restrictions	-26.89	0.0156	*	-15.28	0.1587	
Logsize	-6.87	0.8382		15.68	0.613365	
ROA	-55.74	0.0002	***	-177.63	9.48E-14	***
Inflation	32.27	0.0009	***	-16.34	0.2987	
GDP	-5.80	0.1647		8.85	0.1266	
Unemployment	29.60	1.98E-12	***	31.32	2.35E-12	***

p-value 0.10 – 0.05: +, 0.05 – 0.01: *, 0.01 – 0.001: **, < 0.001: ***

For the regulatory variables we see that all of them are statistically significant in the first version of the model, and the same for all except Activity restrictions when we remove the crisis years. None of them change sign when we switch model, but we notice that the coefficient estimates for Tier 1 and Capital requirements become smaller when crisis years are removed. This indicates that these variables have more explanatory power in crisis times which is interesting because we saw such a sharp increase in risk during this period. One possible reason to this is that banks received big capital injections from regulators during the crisis period. So, risk could increase due to the GFC while capital requirements increase as well.

ROA is negative and statistically significant across both versions of the regression. This is interesting, especially when the coefficient estimate increase by

219 % in the ex-crisis model suggesting that a bank's return on assets become more important in determining risk. Logsize change sign from negative to positive when crisis years are removed, but the results are insignificant in both cases.

Inflation is positive and statistically significant at the 0.1 % level in the first model and it changes sign and loses significant when crisis years are removed. GDP changes sign from negative to positive in the ex-crisis model but remains insignificant across both. Unemployment is positive and statistically significant at the 0.1 % level in both versions of the regression and the coefficient estimate remains similar in size.

7.2 Discussion of hypotheses

We can summarise our results and hypotheses in the following table:

Table 7. Summary table of hypotheses and results

		Merton DDM		CDS	
Variable	**Hypothesis**	**2000 - 2012**	**Ex crisis**	**2004 - 2012**	**Ex crisis**
Tier 1	Increase in Tier 1 capital reduces risk	No	Yes	No (***)	No (*)
Capital requirements	Stricter capital requirements reduces risk	No (**)	No (+)	No (***)	No (**)
Supervisory power	More supervisory power reduces risk	Yes	No (+)	No (**)	No (**)
Activity restrictions	More activity restrictrions reduces risk	Yes	Yes	Yes (*)	Yes
Logsize (a)	A higher log(assets) reduces risk	Yes (**)	Yes (***)	Yes	No
Logsize (b)	A higher log(assets) increases risk	No (**)	No (***)	No	Yes
ROA (a)	Higher return on assets reduces risk	Yes (***)	Yes (***)	Yes (***)	Yes (***)
ROA (b)	Effect is stronger in ex-crisis regression		Yes (***)		Yes (***)
Inflation	A higher change in inflation increases risk	No	Yes	Yes (***)	No
GDP	Higher GDP growth rate reduces risk	Yes	No	Yes	No
Unemployment	Higher unemployment rate increases risk	Yes (***)	Yes (***)	Yes (***)	Yes (***)

p-value 0.10 – 0.05: +, 0.05 – 0.01: *, 0.01 – 0.001: **, < 0.001: ***. "Yes" indicates that the sign of the coefficient estimate is in line with our hypothesis, "No" indicates the opposite.

Tier 1:

We hypothesised that a higher Tier 1 capital ratio would decrease risk since it provides banks with a bigger capital buffer. The results in the DDM version were mixed and insignificant, and the CDS results indicate the opposite of our hypothesis: a higher Tier 1 capital increases risk as measured through CDS spreads. One reason for this weak result might be that banks don't vary their Tier 1 capital ratio too much once they reach the regulatory standard.

Capital requirements:

Originally, we thought that stricter capital requirements would lead to a decrease in riskiness. However, we see that across all four versions of the regression, our results indicate that stricter capital requirements increase risk when measured through the DDM or CDS spreads. This, along with the results we got for Tier 1 suggests that capital requirements are not the most effective tool for regulators. However, we know that banks can quickly exchange safe assets for riskier one or move their assets to areas with fewer regulations and exploit loopholes in what is called regulatory arbitrage. This could be a partial explanation as to why this regulatory measure is ineffective for our sample.

Supervisory power:

Our hypothesis was that if regulators had more supervisory power, then the risk of banks in that area would decrease. That is not the case according to our results. In three out of four regressions, the coefficient estimate suggested that more supervisory power increases risk. This is more surprising than the result above since this means that regulators have more power to directly intervene in the day-to-day activities of the banks. One reason why these results arise is that regulators do not use the tools at their disposal to their maximum effect. This could allow banks to move into grey areas that current regulation do not cover, such as the securitisation activities we saw previous to the GFC.

Activity Restrictions:

The results we have obtained for activity restrictions are in line with our hypothesis, i.e., that more restrictions on which activities banks can engage in lower risk. However, the coefficient estimate was only significant at the 5 % level when CDS was the dependent variable and the crisis years were included. Since the rest of the versions had insignificant results, we cannot make any definite conclusion. However, these results seem to suggest that activity restrictions are the most powerful tool in reducing bank risk.

Logsize:

We decided to include a dual hypothesis with regards to asset size due to the differing results obtained in previous studies that looked at effects of size on risk. Our results suggest that size reduces risk for banks in our sample. The results are particularly strong when DDM is the dependent variable where the coefficients are significant. These results suggest that the diversification and efficiency benefits of size outweigh the moral hazard effect.

Return on assets:

This variable obtained one of our best results. We predicted in our hypothesis that a higher return on assets would lead to lower risk. The coefficient estimates confirm that this is the case and they are statistically significant at the 0.1 % level in all four versions of the regression. Our results also support the twin hypothesis we made. The effects are much larger in the ex-crisis models.

Inflation:

The results we obtained for inflation are mixed. We get a coefficient estimate in line with our hypothesis when CDS is the dependent variable and all years are included that is statistically significant at the 0.1 % level. However, the results are statistically insignificant in three out of four of the remaining versions. Therefore, we can’t conclude as to what effect changes in inflation has on bank risk.

GDP:

The coefficient estimates for GDP were in line with our hypothesis when all years were included for both dependent variables. However, the results change when crisis years are excluded and none of the four coefficients are significant at any confidence level. This could be because GDP growth rates are usually a lagging indicator of economic downturns. Therefore, when we remove crisis years and run the regression, the drop in GDP growth rate will happen after risk has gone up. This leads to it having low predictive power.

Unemployment:

This variable, along with return on assets, is where we obtained the best results. The coefficient estimate is statistically significant at the 0.1 % level and in line with our hypothesis in all four versions of the regression. Here we might see the opposite of what happens for GDP growth rate if unemployment is a leading indicator of economic downturns.

7.3 Robustness of results

We perform several tests to check the robustness of the results.
First, we use the F-test to check whether the fixed effects are needed. Under the null hypothesis there are no major bank-specific characteristics. The alternative hypothesis states there is a substantial interbank variation and fixed effects model is more appropriate. We subsequently run a Hausman test to check whether unique errors (u_i) are correlated with the regressors and decide whether to use random effects model, should endogeneity be detected. Finally, we check for heteroscedasticity to see whether too much of the variance is explained by additional explanatory variables. We do not test for autocorrelation due to the limited timespan of the sample. The results are summarized in tables below.

Table 8. Summary of robustness checks for 2000-2012 MDD panel

Test		F-test	Hausman Test	Breush-Pagan
Purpose		Fixed effects vs polled OLS	Fixed effects vs Random effects	Test for Heteroskedasticity
Hypothesis	Null	No fixed effects	Random effects are preffered	Homoskedasticity
	Alternative	Significant effects	Fixed effects are preffered	Presence of Heteroskedasticity
P-value		9.166E-11	0.001594	0.1199
Rejection rule		< 0.05	< 0.05	< 0.05
Result		Reject the null	Reject the null	Fail to reject the null

We see in table 8 that the tests confirm our choice of a fixed effects model as significant variation between banks was detected. However, in pooled OLS regression we observed no differences in sign of coefficients and no major ones in terms of the significance of the results. The full breakdown and side-by-side comparison can be found in appendix C.

Similarly, we confirm that fixed effects model specification is a robust choice for the model using CDS spread as a risk proxy. The summary is in table 9.

Table 9. Summary of robustness checks for 2004-2012 CDS panel

Test		F-test	Hausman Test	Breush-Pagan
Purpose		Fixed effects vs polled OLS	Fixed effects vs Random effects	Test for Heteroskedasticity
Hypothesis	Null	No fixed effects	Random effects are preffered	Homoskedasticity
	Alternative	Significant effects	Fixed effects are preffered	Presence of Heteroskedasticity
P-value		3.991E-08	5.405E-08	2.2E-16
Rejection rule		< 0.05	< 0.05	< 0.05
Result		Reject the null	Reject the null	Reject the null

However, we detect a presence of heteroscedasticity by rejecting the null hypothesis that the data is homoscedastic. Kleiber and Zeleis (2008) say that in such regression coefficients can still be estimated consistently but first a consistent covariance matrix must be computed. We apply this methodology to estimate the heteroscedasticity-consistent coefficients. Tier one and Inflation have a reduced significance level and ROA becomes insignificant altogether. Supervisory power has an increased significance. The rest of the results does not differ substantially. The output can be found in appendix D.

7.4 Further research into this topic

It would be interesting to replicate this study for more countries and regions since our study revolves around European banking regulation and its effectiveness. This would then allow for a more granular analysis and expanded discussion about the relationship between regulation and risk. We were also significantly limited by the availability of data. Longer regulation survey would also allow to test the effects for a longer time period after the great financial crisis. In our thesis we were limited to the timespan of twelve years. Also, the same study can be done using other dependent variables to see if the results remain the same.

8. Conclusion

Among the regulatory variables we included in our study we must conclude that capital requirements and supervisory power are the best predictors for bank risk. However, the results are in contradiction with our original hypothesis, i.e., that stricter regulation reduces risk in the banking sector. We can see from figure 1 how credit offered by banks increased sharply after the GFC hit due to capital injections by central banks, which would mean that banks must gradually offer riskier loans so that overall risk increases. This could explain some parts of why the result indicates that stricter regulation increases risk since the indices are rising after the GFC. Activity restrictions, the only variable consistently suggesting that stricter regulation reduces risk, is statistically insignificant in three out of four of the regression, thus not allowing us to make a definitive conclusion as to what effect it has on bank risk. However, the coefficient estimate indicates that this is the most effective way that regulators can reduce risk.

The results we obtained for our bank-specific controls were largely in line with our hypotheses. Return on assets proved to be one of the best predictors of bank risk and we found evidence in support of both of our hypothesis. Namely that better return on assets reduces risk, and that this effect is particularly powerful when we exclude the euro crisis years. This is expected considering that the risk of bank failures is based on the notion that banks have a capital buffer to handle losses. If these losses do not incur, then the bank will not fail. The results for Logsize are only statistically significant when DDM is the dependent variable, and they suggest that bigger banks are less risky than smaller banks. This result points in the direction of benefits of size outweighing the moral hazard effect.

Unemployment was the only macro control that showed strong significance and consistent results in line with our hypothesis. We predicted that a higher unemployment rate increases risk in the banking sector. This is as expected since unemployment and downturns in the wider economy are closely correlated. The results for Inflation and GDP are mixed, so we cannot make a conclusion as to what effect they have on bank risk. However, it is important to include these variables in the regression to control for any effect they might have had on our sample.

Based on this data, we can conclude that the regulatory measures employed for the sample period in Europe are not the most effective in reducing risk in the banking sector. Rather, these regulations could lead to higher risk. Our finding suggests that a bank-specific variable such as return on assets and a macro variable such as unemployment is more significant in determining risk in the European banking sector.

Appendix

Appendix A.

The model inputs for Merton distance to default were calculated as following. Liability threshold was calculated according to the method used by Bharath et al. (2008)

$$Value\ of\ equity = \frac{(No.of\ shares\ outstanding_{t-1} + No.of\ shares\ outstanding_{t})}{2} * Average\ stock\ price_t$$

$$Volatility\ of\ returns_t = \ Standard\ deviation(Returns\ in\ the\ year\ t)$$

Risk-free rate was downloaded from Bloomberg for the respective countries.

$$Total\ short-term\ debt = Total\ deposits + Short\ term\ secs\ and\ borrowings\ sold\ under\ repo$$

$$Liability\ threshold = Total\ short-term\ debt + 0.5 * (Total\ debt - Short-term\ debt)$$

dT was set to 1 and the drift parameter in the model was set to last year's return on assets.

Appendix B.

Questions in the Activity Restrictions Index. (From Barth et al., 2011)

1. **Securities Activities**

The extent to which banks may engage in underwriting, brokering and dealing in securities, and all aspects of the mutual fund industry. (Higher values indicate more restrictive.)

a = 1; b = 2; c = 3; and d = 4. 4.1

What are the conditions under which banks can engage in securities activities?
a. A full range of these activities can be conducted directly in banks,

b. A full range of these activities are offered but all or some of these activities must be conducted in subsidiaries, or in another part of a common holding company or parent,
c. Less than the full range of activities can be conducted in banks, or subsidiaries, or in another part of a common holding company or parent,
d. None of these activities can be done in either banks or subsidiaries, or in another part of a common holding company or parent.

2. **Insurance Activities.**

The extent to which banks may engage in insurance underwriting and selling. (Higher values indicate more restrictive.)

a = 1; b = 2; c = 3; and d = 4. 4.2

What are the conditions under which banks can engage in insurance activities?
a. A full range of these activities can be conducted directly in banks,
b. A full range of these activities are offered but all or some of these activities must be conducted in subsidiaries, or in another part of a common holding company or parent
c. Less than the full range of activities can be conducted in banks, or subsidiaries, or in another part of a common holding company or parent,
d. None of these activities can be done in either banks or subsidiaries, or in another part of a common holding company or parent.

3. **Real Estate Activities**

The extent to which banks may engage in real estate investment, development and management. (Higher values indicate more restrictive.)

a = 1; b = 2; c = 3; and d = 4. 4.3

What are the conditions under which banks can engage in real estate activities?
a. A full range of these activities can be conducted directly in banks,

b. A full range of these activities are offered but all or some of these activities must be conducted in subsidiaries, or in another part of a common holding company or parent

c. Less than the full range of activities can be conducted in banks, or subsidiaries, or in another part of a common holding company or parent

d. None of these activities can be done in either banks or subsidiaries, or in another part of a common holding company or parent.

Appendix C

	Pooled OLS Merton 2000-2012			Pooled OLS CDS 2004-2012		
Coefficients	**Estimate**	**p-value**	**Significance**	**Estimate**	**p-value**	**Significance**
(Intercept)	-0.2051	0.8973		680.5	0.0015	**
Tier 1	-0.0243	0.6111		17.9	0.0007	***
Capital requirements	-0.0587	0.3146		13.3	0.0643	+
Supervisory power	0.1171	0.0420	*	7.9	0.2439	
Activity restrictions	0.0364	0.5747		-5.0	0.4972	
Logsize	0.0701	0.5063		-75.0	2.76E-06	***
ROA	0.9781	0.0000	***	-112.2	1.70E-11	***
Inflation	0.3552	0.0001	***	24.8	0.0149	*
GDP	0.0214	0.6436		-5.6	0.2429	
Unemployment	-0.0502	0.0882	+	17.0	3.69E-07	***

Appendix D

Heteroscedasticity-consistent coefficients for 2004-2012 CDS Panel.

Coefficient	**Estimate**	**p-value**	**Significance**
Tier 1	17,1982	0,0739313	.
Capital requirements	37,7723	9,41E-05	***
Supervisory power	24,2808	0,0008316	***
Activity restrictions	-27,1424	0,0175997	*
Logsize	-3,9996	0,8869606	
ROA	-53,9295	0,1638225	
Inflation	32,6726	0,0031481	**
GDP	-3,6349	0,5445413	
Unemployment	30,7866	0,0004001	***

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