Systemic risk and bank equity valuation

A study of the market-to-book value and government guarantees

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Abstract

In previous research, it has been argued that a link exists between the equity valuation of a bank and its tail risk. The relationship has been attributed to government guarantees and how they create a synthetically low cost of debt, which increases the incentive to take on risk. In this thesis we use two approaches to further explore the relationship between government guarantees and equity valuations in the banking sector. Firstly, we focus on the previously identified positive relationship between the market-to-book value (MBV) and tail risk in US banks and examine whether such a relationship exists in the European financial market. Our findings imply that investors priced government guarantees in the market value of equity of both US and European banks prior to the 2008 crisis, but more so in US banks. Secondly, we study whether the variations in the MBV is driven by expected government guarantees or a bank's performance quality and find a positive relationship for both of our proxies. When the proxy for government guarantees, the GG estimate, is analysed further we discover that its positive relationship with the MBV is mainly driven by its CDS spread component, implying that increased risk leads to a lower equity valuation. To summarise, we find additional evidence that banks with a higher MBV carry more tail risk but cannot empirically prove that a higher MBV is due to anticipated government guarantees. Instead we find that riskier banks are valued less by investors and that the relationship between government guarantees and the MBV remains ambiguous.

Keywords: Government guarantees, Banks, Market-to-book value, Systemic risk, Financial crisis

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1 Introduction

The financial crisis in 2008 marked a renewed interest in government interventions in the financial market, along with a debate on their desirability. What started out as losses in the US home mortgage market quickly evolved into a global economic downturn, with numerous banks defaulting on their debt obligations. Consequently, different forms of government guarantees emerged in an attempt to stabilise the economy and prevent a deeper systemic crisis. Even though government guarantees are aimed at reducing default risk, they are also argued to incentivise excessive risk-taking, which might ultimately lead to magnified systemic risk exposures for the overall economy. This thesis aims to deepen the understanding of government guarantees and their link to equity pricing through two research questions: (1) Did market participants anticipate government guarantees when making investment decisions in European banks prior to the 2008 crisis, and (2) To what extent do government guarantees drive the market-to-book value (MBV) and how much does performance quality affect the market value of equity.

It has been argued that equity investors in the US attribute value to government guarantees (Atkeson et al., 2018) as they imply an artificially low cost of debt in relation to bank risk-taking, leading to higher equity valuations for risky banks. However, the validity of this statement in European and other international markets is yet to be determined. The interconnectedness between the European and US banking sector, along with them experiencing similar levels of government intervention around the 2008 crisis, triggers the belief that investors' perception of bank equity should be comparable across the two regions. Nevertheless, the regional differences within Europe raise the question whether such investor expectations exist and if they are robust. Following the methodology in Meier and Meng (2018), a regression analysis is used to explain tail risk returns through reported MBV for 132 listed European banks. We find a positive relationship between the MBV and tail risk, but that the relationship is more prevalent for US banks. The stronger relationship in the US financial sector is argued to be due to US banks being more systemically important to the global economy. We also find evidence of the ROE being a better predictor of tail risk in European banks than in US banks. One explanation to this could be the mixed regulatory and accounting standards within Europe, which causes the MBV to not reflect consistent definitions across firms. Therefore, investors look at "cleaner" metrics such as the ROE when valuing European banks.

The second part of the thesis aims to further explore the link between the MBV and anticipated government guarantees in the US market. Following the argument of Schweikhard and Tsesmelidakis (2011), expected government guarantees have been estimated through the difference between actual credit spreads and implicit CDS spreads, which are constructed through option pricing. We have used a government guarantee estimate to explore whether the variation in banks' MBV can be attributed to the expectations of future government guarantees. Our results indicate that the relationship between the government guarantee estimate and MBV is mainly driven by the negative correlation between the MBV and actual CDS spreads. Thus, the findings imply that risky banks are valued less by investors.

The rest of this thesis is structured as followed: In Section 2 we provide background information regarding the research questions at hand. Section 3 summarises the relevant theories used for the study, followed by Section 4 that explains the theoretical model used to analyse the relationship between systemic risk, government guarantees and the variables of interest. Thereafter, Section 5 presents the hypothesised results and Section 6 explains the methods used for the execution of the study. Finally, Section 7 and 8 presents the descriptive statistics and results for the first and second research question respectively, and Section 9 concludes the thesis.

2 Background

2.1 Systemic risk and government guarantees

The global economic contraction that was seen during the 2008 crisis highlighted the vital role that banks have in facilitating economic growth and financial stability within the broader economy. Systemic risk – the risk of a company-level event triggering instability to the entire financial system and possibly the collapse of the broader economy – was a great contributor to the level of distress within the financial sector during the crisis. Consequently, the concept of "Too-Big-To-Fail" (TBTF) became evident after the crisis. The concept of TBTF refers to the idea that there are some financial institutions that are so large and interconnected that their bankruptcy would cause a systemic collapse to the global economy. Therefore, the government needs to intervene and offer support during times of crisis (Gormley et al., 2011) to restore financial stability. Various forms of government intervention have emerged over the years, but the 2008 crisis is seen to have triggered a renewed interest in government guarantees, along with a debate on their desirability.

The systemic risk exposure of the banking sector and the need for government guarantees can be explained through the characteristics of banks' businesses and their role in society. Banks serve a financial intermediary function in the economy by: (1) taking deposits on the liability side of the balance sheet and (2) using the funds to grant loans on the asset side. Holding long-duration assets and short-duration liabilities, implies that banks have to refinance their balance sheets before their assets have matured. Consequently, if the assets decline in value, refinancing becomes expensive (Bullard et al., 2009). Besides taking deposits, banks also finance themselves through debt and interbank lending. In the interbank market, banks can lend and borrow to each other, mostly on a short-term basis, where loans have maturities between one day (overnight) and six months. The market for interbank lending helps banks manage interest- and exchange rate risk, as well as netting out differences in liquidity needs (Bank for International Settlements, 1983). As the interbank lending market is based on the financial industry providing capital to itself, the system is vulnerable to sector-wide liquidity problems (Bank for International Settlements, 1983), thus increasing systemic risk. Additionally, banks generally have higher leverage compared to other industries (Marqueza et al., 2015), which can cause even modest declines in asset values to result in insolvency for the bank. As the bank acts as a financial intermediary, this can also have spillover effects to the rest of the economy.

Government guarantees are aimed to mitigate potential spillover effects to the rest of the economy and increase financial stability during systemic events. There are two types of government guarantees – explicit and implicit. Explicit guarantees involve a promise, or obligation, by the state to compensate certain stakeholders in case a bank fails to meet its obligations to the stakeholder. An example of an explicit guarantee is Federal deposit insurance, which protects deposit holders of a bank up until a predetermined level (Bullard et al., 2009). It has been proven that this type of government guarantee encourages risk-taking, as it reduces the incentive for depositors to monitor the amount of risk that a bank is taking on (Merton, 1977). Implicit guarantees involve the expectation that the state will salvage or provide funding to save institutions or to put up guarantees for a specific asset class, once a crisis occurs. This thesis will be referring to government guarantees as both explicit and implicit guarantees.

2.2 The financial crisis and government guarantees

The global financial crisis started with losses in certain home mortgage markets in the US. However, as many European banks were heavily invested in the US banking sector around the time of the crisis, the European financial sector was indirectly affected by the US mortgage crisis (European Commission, 2009). Within Europe, some countries' financial systems were more affected than others. For example, Iceland was hit hard by the crisis, mainly due to its financial system's dependence on foreign asset exposures. German banks suffered large losses during the crisis due to the recent shift toward financialisaton and derivatives trading, which was originally introduced to increase profitability (Hodson and Quaglia, 2009). Hardie and Howarth (2009) have found evidence that French banks had less foreign ownership, as well as low involvement in risky securities at the point of the crisis. They argue that this is a probable cause for the resilience displayed by the French financial sector during the crisis.

The crisis also revealed how governments in the US and Europe responded to the systemic failure of the banking sector by providing financial aid. The US government supported banks both through legislative actions, including the Troubled Asset Relief Program (TARP Act), and by actions taken by the US Federal Reserve. These efforts were directed both toward troubled asset

classes – such as asset relief programs, QE-programs[1] and asset purchases – as well as bailouts directly aimed at specific firms – such as the bailout of Bear Stearns; loan-loss backstop protections for Bank of America and Citigroup and providing bridge loans to American International Group. In total, $3 trillion was effectively invested in government aid programmes during the crisis (Schweikhard and Tsesmelidakis, 2011).

In Europe, large initiatives were also put into place to recapitalise and provide asset relief to the struggling banking sector. Between the years of 2008 and 2012, €591.9 billion was provided by member states to the financial sector in the European region. Furthermore, liquidity support in terms of deposit insurance and other explicit guarantees amounted to a total of €2 billion but were estimated as high as € 906 billion in 2009. In Europe, the amount of government support varied by country. The four countries providing the most capital support during the crisis were the UK (€82 billion), Germany (€64 billion), Ireland (€63 billion), and Spain (€60 billion), amounting to approximately 50% of the total capital support. The top receiving banks were RBS (€46 billion), Anglo Irish Bank (€32 billion) and Bankia (€22 billion) (Colombani and Gonzalez Iglesias, 2013).

[1] QE, Quantitative easing, is a monetary policy action, where a central bank purchases securities from the market to increase money supply and encourage lending and investments.

3 Theory

This thesis is divided into two research topics: 1) Can European banks' market-to-book value (MBV) predict tail risk and thus, are government guarantees drivers of the market value of equity? and 2) Do investors attribute shareholder value to government guarantees during non-crisis periods and hence, can the estimated value of government guarantees be used to estimate the MBV directly? The first research question will be referred to as "Estimating tail risk" and the second "Explaining the market-to-book value". This section will elaborate on the background of the intended studies and the previous research that relates to the two research questions at hand.

3.1 Estimating tail risk

Meier and Meng (2018) aimed to study whether market participants priced in government guarantees when valuing their investment opportunities before the financial crisis, as well as measuring the extent to which the market value of banks' equity can predict systemic risk. They find a significant positive correlation between a bank's MBV and exposure to systemic risk, suggesting that market participants anticipated government guarantees when valuing bank equity prior to the 2008 crisis. Additionally, they argue that the positive relationship indicates that the MBV can act as a proxy for systemic risk, which has also been proven in prior research (Fama and French, 1992). As Meier and Meng (2018) studied US banks, this thesis aims to see if their findings are applicable to the financial system in Europe as well.

3.1.1 Tail risk

Both systemic- and tail risk are proxies for the risk exposure of banks. However, whilst systemic risk represents the risk for the whole financial system, tail risk measures the risk exposure banks have on an individual level (Meier and Meng, 2018). This thesis aims to contribute to the understanding of the model-free approach of estimating tail risk, using an ex-ante measurement. To do so, an understanding of model-based approaches, their advantages and drawbacks are needed.

In hindsight, one can more accurately analyse the impact that a crisis had on individual banks, as well as the market as a whole. The marginal expected shortfall (MES) has been used as

a proxy for tail risk (Acharya et al., 2017), which measures the expected loss of a bank when the market experiences extremely bad performance. However, it is found that the MES lacks the ability to provide insight ex-ante and that standard balance sheet metrics are better predictors of bank losses in true crisis times (Idier et al., 2014).

Even though the current and actual tail risk is hard to estimate, there have been numerous studies trying to predict tail risk before a crisis. One ex-ante method is the change in the conditional VaR (ΔCoVaR), which is aimed at analysing the interdependence of banks within the whole financial system (Brunnermeier et al., 2011). The ΔCoVaR measures the change in the VaR of the entire financial system, given that an individual financial institution is under distress. Furthermore, Bostandzic et al. (2014) measure the probability of both the return of the market and of the individual bank being in the lower tail of the distribution – also known as lower tail dependence (LTD). The Basel Committee on Banking Supervision (BCBS) has previously used the VaR-method to estimate a bank's risk exposures. The VaR is a model-based, ex-ante approach and estimates the amount of losses that may be incurred during a set time period, given normal market conditions. In other words, the VaR is the most a bank can lose in extreme events, with a confidence of 1-a:

$$Pr(R < -VaR_a) = a$$

However, the drawbacks of using the VaR is that it assumes a distribution based on normal market times, which can lead to undercapitalized book exposures during crisis times (Basel Committee on Banking Supervision, 2014). Consequently, the BCBS altered their calculation of tail risk to using the expected shortfall (ES) approach, which would better relate to periods of bad losses. The expected shortfall (ES) can be used to quantify the risk of a portfolio and represents the amount of losses that are greater than the value at risk (VaR).

$$ES_a = -E[R|R \leq -VaR_a]$$

Even though the ES is better at reflecting bad market days in the past, it is not able to incorporate the current situation and the systemic risk within individual banks (Allen and Saunders, 2004).

Meiselman et al. (2018) argue that the fault in risk exposure calculations do not lie within a particular model, but rather that any quantitative method is prone to manipulation as long as there

is a desire to do so. To correct for this, Meiselman et al. (2018) propose a model-free approach in measuring tail risk based on profit ratios, as ratios don't measure tail risk exposure directly (Meier and Meng, 2018) and the only way a bank can be seen as less risky is if it under-reports its profits. Moreover, according to Meiselman et al. (2018), it is possible to reveal systemic risk exposures of individual banks using tail returns during crisis events. Systemic risk exposures are not directly observable through market returns since systemic risk concerns the interdependence between banks. However, crisis periods can be interpreted as systemic events and thus, a bank's return during a crisis can also be interpreted as systemic risk exposure. This thesis, like Meier and Meng (2018), aims to expand on the idea of a model-free approach by analysing the significance of the MBV ratio as a proxy for tail risk in European banks ex-ante.

The benefit of using the MBV is that investor perceptions will be accounted for, allowing the exploration of whether government guarantees were anticipated by the market before the financial crisis. The market value of equity is driven by the perceptions of investors, whilst the book value of equity is the accounting value that is reported on balance sheets. If market participants anticipate government guarantees then they will value the bank's equity higher than the accounting value, leading to a MBV ratio above 1 (Meier and Meng, 2018).

3.1.2 Government guarantees

The high leverage observed in banking is partly argued to be the result of deposits being subsidized by publicly provided deposit insurance (Cline, 2015). According to the Modigliani Miller (MM) theorem, capital structure is irrelevant when determining the value of a firm, as the risk premia of debt- and equity holders will shift according to the amount of leverage that the firm is taking on. The MM theorem assumes perfect market conditions but is often used as framework to conceptualise the impact of imperfect capital market components. For example, taxes and costs of distress are both components of imperfect capital markets, where the presence of taxes incentivise firms to take on leverage and costs of distress limits the optimal level of debt in the company. The existence of government guarantees causes the costs of financial distress to be artificially low, resulting in leverage to be beneficial for the bank (Juks, 2010). Furthermore, as the state partially bears the cost of debt, government guarantees can also generate excessive returns to the bank shareholders. This is further explained in Section 4, when we construct our theoretical model.

There is currently a debate about the desirability of government guarantees and their impact on the economy. One benefit of government guarantees is that they provide security against bankruptcy and reduce the risk of spillover effects from one institution to the whole economy. However, the guarantees may also encourage excessive risk-taking by the banks, causing increased costs for the respective governments in case a bailout is needed (Allen et al., 2017). This moral hazard problem may impact the financial stability of an economy. However, some also argue that there is a need for a certain amount of risk-taking as it allows banks to provide more liquidity transformation, which is welfare improving (Allen et al., 2017).

It is believed that many investors prior to the financial crisis priced in government guarantees when making their investment decisions (Meier and Meng, 2018; Atkeson et al., 2018; Kelly et al., 2016). Kelly et al. (2011) study the increased spread between out-of-the-money put options on a basket of individual banks and puts on the financial sector index, arguing that the divergence in prices is related to government guarantees. The basket of banks is exposed to individual bank risk and it is not certain that a government bailout may be sufficient for its survival or that its failure is sufficient to trigger government intervention. As implicit bailout guarantees offers security for the entire financial sector the index is more protected in case a crisis occurs. In other words, there is a chance of each individual firm within an economy to default in a crisis, but the entire financial system will not fail. Consequently, the index option should trade at a higher price than the option on the basket of individual banks. As a result, Kelly et al. (2011) argue that the increasing spread between the two options is due to government guarantees being anticipated by market participants when evaluating their investment decisions.

3.1.3 Market-to-book ratio

As many of the assets held by banks are traded assets and are thus reported marked-to-market, a bank's accounting value of equity should equal its market value, resulting in a MBV equal to one. However, this is not always the case and it is often due to investors pricing in intangible qualities into the market value of equity. This causes the market value to be greater than the accounting value and consequently a MBV greater than one. Another explanation to a higher MBV could be exceptional market conditions (Bogdanova et al., 2018) or implicit government guarantees (Atkeson et al., 2018).

Atkeson et al. (2018) show that the high valuation of bank' market value of equity prior to the 2008 financial crisis was greatly driven by the support from government guarantees. Additionally, they provide evidence of the value of government guarantees to bank equity being extremely sensitive to the risk exposure of bank assets. The increased regulatory capital that was enforced after the crisis has led to decreased risk-taking in banks, not allowing the banks to exploit the benefits of the government guarantees to the same extent as before the crisis. As a result, it is argued that the stricter regulations are harming bank profits and thus leading to a lower post-crisis MBV.

3.1.4 Profitability and price-earnings ratios

Return on assets (ROA) and the return on equity (ROE) are both measures of firm profitability. The profitability measure ROA measures how well a company utilizes its assets and is calculated by dividing the earnings before interest and expense (EBIE) by the book value of assets (Meiselman et al., 2018). Contrary, ROE measures how efficiently a company is in generating shareholder value and is equal to the company's net income to its book value of equity. The main difference between ROA and ROE is that ROA takes a company's debt and equity into account, whilst ROE focuses on the earnings generated solely to the company's shareholders. It is assumed that both ROE and ROA will increase in an economy facing normal market conditions and fall when there is a crisis (Meier and Meng, 2018). However, Meiselman et al. (2018) argue that ROE is the preferred profitability measure when analysing banks' risk due to any systematic risk exposure of a bank's asset portfolio being magnified by leverage, which is the same effect that leverage has on ROE. This thesis will evaluate both profitability ratios to explore if this statement holds for European banks as well. The Price/Earnings (P/E) ratio combines the market valuation of a firm with its reported earnings and can be used by investors to identify mispriced stocks. Mathematically, P/E multiplied by ROE constitute a firm's MBV, indicating that all the information in the product of ROE and P/E exists within the MBV (Penman, 1996).

3.2 Explaining the market-to-book value

Previous research has already indicated that there is a positive relationship between MBV and tail risk, at least in the US. It is hypothesised that additional value attributed to companies carrying

more risk pre-crisis, is derived from expected government guarantees (Meier and Meng, 2018). The value that investors allocate to expected government guarantees is not directly observable and therefore has to be measured through other variables. Atkeson et al. (2018) argue that the valuation of banks can come from two sources – the franchise value (FV) and government guarantees (GG). In this section, we aim to find the appropriate variables to distinguish between the FV and GG, using existing theory on how market participants value banks, and the financial instruments associated with both firm equity and debt. We also present a framework of how to estimate government guarantees using option and CDS pricing.

3.2.1 Return on assets

In this study we will aim to differentiate the quality component of a bank's operations and the value associated with government guarantees. A company is deemed efficient by investors if it can generate an adequate return while using the minimum amount of assets to do so (Bragg, 2012). Further, Needles et al. (2013) define ROA as a measure that shows how efficiently a company uses its assets to produce income. Thus, we will use ROA to proxy for bank quality when trying to explain the variation in the MBV.

3.2.2 Credit default swaps

Credit default swaps (CDS) can act as a proxy for the amount of credit- and default risk in a bank. Simplified, CDS contracts provide protection to the buyer from a bank defaulting on their debt obligation – caused by events including bankruptcy, failure to pay their obligations or a restructuring event. According to Blanco et al. (2005), CDS spreads provide a more accurate prediction of credit risk than bond yields. Bond spreads are greatly affected by liquidity- and interest rate risk, along with short-sale restrictions, which is why structural factors are better reflected in CDS spreads (Ericsson et al., 2005; Blanco et al., 2005). Additionally, CDS are standardized products, while bond yields vary with respect to their time to maturity, covenants and options, which limits the ability to gather homogenous default estimates (Schweikhard and Tsesmelidakis, 2011). Thirdly, Longstaff et al. (2005) have shown that CDS premiums react faster to changes in the credit conditions of the underlying firm. Thus, several studies have concluded that CDS spreads act as good predictors of bank default risk.

3.2.3 Estimating government guarantees using implied volatility

Schweikhard and Tsesmelidakis (2011) argue that the market price of default risk differs across credit and stock markets. As government guarantees are primarily aimed towards the protection of debtholders, the stock-market-implied default risk would be greater than the one implied for creditors. Estimating government guarantees is a challenging task but it is argued that the market-implied government guarantee can be estimated by comparing options and CDS spreads (Jobst and Gray, 2013; Schweikhard and Tsesmelidakis, 2011). CDS spreads can be used as a proxy for credit losses and thus reflect the expected losses associated with default, net of any financial guarantees. Conversely, put options are argued to incorporate the expected losses gross of government guarantees, as equity prices are not protected in a default event. The difference between option pricing and the actual CDS spreads can be converted to a common unit to reflect the value of the government guarantee. Schweikhard and Tsesmelidakis (2011) refer to a default threshold (B) that caps the maximum debtholder loss in a crisis. They thereafter use the implied volatility of stock options to calculate an implied CDS spread using the CreditGrades methodology (Finger, 2002), which does not incorporate any loss limits, as government guarantees are aimed at debt holders, not equity holders. Their resulting model is explained below.

The default threshold B equals LD, where L is defined as the average recovery rate of firm debt D. However, the barrier (B) is not revealed until default actually occurs, and this uncertainty is reflected in L, which follows a lognormal distribution with mean $\bar{L}$ and standard deviation λ. Following this model, the risk-neutral survival probability P(t), reflecting the probability of the firm value not reaching the default boundary until time (t), can be written as:

$$P(t) = \Phi\left(-\frac{A_t}{2} + \frac{\log(d)}{A_t}\right) - d \times \Phi\left(-\frac{A_t}{2} - \frac{\log(d)}{A_t}\right)$$

where Φ () is the cumulative normal distribution function, and

$$d = \frac{S_0 + \bar{L}D}{\bar{L}D} exp\ \lambda^2$$

where d, scaled variance of the default barrier is equal to the variance of λ, scaled by current stock price and the default barrier for the individual bank.

$$A_t = \sigma_V^2 t + \lambda^2,$$

σ_V indicates the asset volatility:

$$\sigma_V = \sigma_S \frac{S}{S + \bar{L}D}$$

and σ_S denotes the implied volatility of the stock option and S the stock price.

The valuation of CDS involves calculating the present value of the premium leg and contingent leg. The premium leg, or fixed leg, involves fixed fee payments and the contingent leg refers to the payments at the time of default. Both legs are calculated based on the amount that has to be covered at time of default and the cumulative survival probability until time (t). Thus, the premium c of a CDS with maturity T can be expressed as:

$$c = r(1 - R)\frac{1 - P(0) + e^{r\xi}G(t + \xi) - G(\xi))}{P(0) - P(t)e^{-rt} - e^{r\xi}G(t + \xi) - G(\xi))}$$

where $\xi = \frac{\lambda^2}{\sigma^2}$, r is the risk-free interest rate, R is the expected recovery rate to a specific debt class and the function G is given by:

$$G(u) = d^{z+\frac{1}{2}}\Phi\left(-\frac{\log(d)}{\sigma_V\sqrt{u}} - z\sigma_V\sqrt{u}\right) + d^{-z+\frac{1}{2}}\Phi\left(-\frac{\log(d)}{\sigma_V\sqrt{u}} + z\sigma_V\sqrt{u}\right)$$

with $z = \sqrt{\frac{1}{4} + \frac{2r}{\sigma_V^2}}$

The difference between the implied CDS spread and the actual CDS spread would reflect the added value obtained from government guarantees. For the complete derivations of the above equations, please see Finger et al. (2002).

4 The theoretical model

As this thesis is a replication and extension of Meier and Meng (2018), a similar theoretical model will be used to analyse whether the MBV can act as a proxy for bank risk, which is a simplified version of Atkeson et al. (2018).

4.1 The two-state model

There are two actors within the model: (1) the bank (B), and (2) the debtholder or financier (F), who require a return of R^f. It is assumed that there is an existing equity holder of the bank who is not investing new money in the new portfolio. As debtholders have seniority over the equity holders, their claims are paid back before any means are distributed to equity. Thus, the equity holder receives the residual claim, if there is any, after the debtholders has received their required returns.

Considering a two-state model, the bank can choose to invest in a safe or a Risky portfolio in the first state. The first and current state is known but the second state is unknown as the payoffs rely on whether the future state is normal (n) or a crisis (c). It is assumed that the NPV of both portfolios are zero, to make them comparable. This means that an investor would be indifferent to invest in either of the portfolios, as the expected return (E(R)), is the same for both. Additionally, to make the portfolio a good representative of the value of the bank, it is assumed that the bank carries one portfolio only.

State	**Probability**	**Returns**	
		Safe Portfolio	*Risky Portfolio*
Normal	$(1-q_c)$	R^f	$R^n > R^f$
Crisis	q_c	R^f	$R^c < R^f$

With the probability of ending up in a crisis state (q_c) we obtain the equations:

$$E(R_{safe}) = (1 - q_c) \times R^f + q_c \times R^f = R^f$$

$$E(R_{risky}) = (1 - q_c) \times R^n + q_c \times R^c$$

As it is assumed that $E(R_{safe}) = E(R_{risky})$, we obtain:

$$(1 - q_c) \times (R^n - R^f) = q_c \times (R^f - R^c)$$

In words, the expected gain from the Risky portfolio in the normal state is equal to the expected loss in the crisis state. There is no excess return or loss in the estimated return for the Risky portfolio.

The Safe portfolio yields the same return in each state, whilst the Risky portfolio generates a return lower than R^f in the crisis state but a return higher than R^f in the normal state. Thus, the Risky portfolio is more volatile than the Safe portfolio.

4.2 Theoretical model – with perfect capital markets

4.2.1 Required return of debtholders

Debtholders require a return on their investment, R^d. In this example, debtholders require the risk-free rate (R^f), thus making $R^f = R^d$. Under perfect capital markets, financiers (debtholders) will adjust their required return to make sure that the expected return is always equal to the required return, R^f. This will result in the following pricing for the two portfolios:

Safe portfolio

Since debtholders' claim on the bank's assets is senior to all other financiers, they will receive R^f in both the normal and the crisis state:

$$E(R^d) = R^f = (1 - q_c) \times R^f + q_c \times R^f$$

Risky portfolio

Debtholders have a claim on the bank's assets senior to all other financiers. However, $R^c < R^f$ in the crisis state, which means that debtholders will not get their required return during a crisis. To compensate for this, the debtholders will require a larger return in the normal state (a higher

interest), which we choose to call R^x. R^x is determined so that the expected return for the debtholders amounts to R^f.

$$E(R^d) = R^f = (1 - q_c) \times R^x + q_c \times R^c$$

Under the assumption $E(R_{safe}) = E(R_{risky})$, there is no excess gain or loss associated with the Risky portfolio (see Section 4.1), resulting in:

$$R^n = R^x > R^f$$

where R^n is the actual returns gained in the normal state for the Risky portfolio.

4.2.2 Residual claims

If the portfolio generates a return after the debtholders have been paid, it will generate a residual claim to the equity holders of the bank $E(R^e)$. However, as previously mentioned, debtholders take all the available returns in both the normal and crisis state. Thus, there is no residual claim for the equity holders in either portfolio, as shown below.

Safe portfolio

$$E(R^{e,safe}) = (1 - q_c) \times (R^f - R^f) + q_c \times (R^f - R^f) = 0$$

Risky portfolio

$$E(R^{e,risky}) = (1 - q_c) \times (R^n - R^x) + q_c \times \max(R^c - R^f; 0) = 0$$

The above implies that equity holders of the risky bank portfolio will have no excess return over equity investors in the safe bank. Thus, the conclusion from this section is that under perfect capital markets, taking on risk is associated with a higher interest rate. Equity holders do not gain from the bank choosing the riskier portfolio.

4.3 Theoretical model – with government guarantees

In the previous model (Section 4.2), we assumed a perfect capital market. This means that there are no tax benefits of debt and that financiers have full information about the returns and probabilities associated with the states of the economy. In reality, it is unlikely for debt holders to hold such comprehensive information, and more likely for the bank to know more about expected future return. This may increase the risk of the moral hazard problem to arise. The absence of taxes and agency issues – such as asymmetric information and government guarantees – is unrealistic but can be used to highlight the impact that market imperfections have on the financial market. In this section we will introduce government guarantees as part of the model, to illustrate its impact on the cost of debt and return to equity holders. The other market imperfections, such as taxes and information asymmetries, are still absent. The return structure and state probability of the two portfolios remain unchanged. However, as will be seen in the following example, the compensation structure for debt holders will change.

The presence of government guarantees means that if the bank cannot meet its obligations to the debtholder, the debtholders will be compensated by the state. If the Risky portfolio returns only $R^c<R^f$, the difference $(R^f - R^c)$ will be provided to the debt holders by the state. In other words, the compensation to debtholders of the Risky portfolio in a crisis state would constitute of the following:

$$R^c + (R^f - R^c) = R^f$$

where R^c is paid by the bank and $R^f - R^c$ is provided through the government guarantees.

4.3.1 Required return of debtholders

For the Safe portfolio, the introduction of government guarantees will have no impact on the return to debt holders, as there will be means to compensate debt holders with R^f in both states. For the Risky portfolio however, the required return by the debt holders will change to R^f, as they are sure to receive R^f in both the normal and the crisis state.

Safe portfolio

$$E(R^{d,safe}) = R^f = (1 - q_c) \times R^f + q_c \times R^f$$

Risky portfolio

$$E(R^{d,risky}) = R^f = (1 - q_c) \times R^f + q_c \times R^c (R^f - R^c)$$

The above implies that, in the presence of government guarantees, the following relationship no longer has to hold: $R^n = R^x > R^f$. When debt holder claims are covered by the government guarantees in the crisis state, the return in the normal state does not need to compensate for the loss in the crisis state. In such a scenario it would be rational for the bank to choose the Risky portfolio as long as $R^n > R^f$. Thus, there is nothing to prevent inefficient allocation of capital that could lead to excessive risk-taking.

4.3.2 Residual claims

Under government guarantees, the Risky portfolio generates a residual claim to the equity holders of the bank ($E(R^e)$), whilst all returns go to the debtholders in the Safe portfolio.

Safe portfolio

$$E(R^{e,safe}) = (1 - q_c) \times (R^f - R^f) + q_c \times (R^f - R^f) = 0$$

Here we see that there is no residual claim associated with the equity holders of the Safe portfolio.

Risky portfolio

$$E(R^{e,risky}) = (1 - q_c) \times (R^n - R^f) + q_c \times max(R^c - R^f; 0)$$

Since $R^n > R^f$ and $R^c < R^f$, the equation can be reduced to:

$$E(R^{e,risky}) = (1 - q_c) \times (R^n - R^f)$$

Thus, the equity holders in the risky bank portfolio receive nothing in the crisis state, but in the normal state they gain the difference between R^n and R^f.

Conclusively, equity holders of the risky bank portfolio will have an excess return over equity investors in the safe bank portfolio in the normal state. Furthermore, the equity holders in the safe bank portfolio will have no benefit in the crisis state, even though the expected return for the two portfolios are the same. This holds true even in the case of $R^n < R^x$, when capital is allocated inefficiently and excessive risk-taking takes place. This is due to the under-pricing of the risky debt that exist under government guarantees. The costs of mispricing are transferred to the state, effectively incentivising the bank to take on more risk.

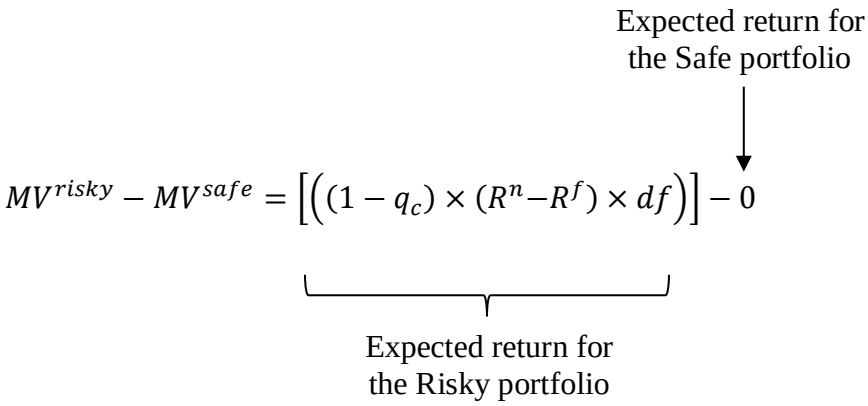
4.4 Market-to-book value

In this section the implications of residual claims under government guarantees will be used to explain why firms with higher risk also should have a larger market-to-book value (MBV). In short, the gains for equity investors in the risky bank, should be reflected in the valuation of the equity stake.

In the initial assumptions of the model, we have already established that, under perfect capital markets, the NPV equals zero for both portfolios.

$$E(NPV) = (CF \times df) - Investment = 0$$

where df is the discount factor. The conclusion from our model with government guarantees (Section 4.3) was that equity holders of the risky bank portfolio receives an excess return – due to the government guarantees subsidising the bank's cost of debt. Consequently, this excess return should be priced into the market value of equity in the risky bank portfolio. The difference between the market value of the Risky portfolio and the Safe portfolio is represented by the equation on the following page.



where MV^{risky} is the market value of the Risky portfolio, MV^{safe} is market value of the Safe portfolio and df represents the discount factor associated with the riskiness of the excess cash flows. As we have assumed that the only imperfection in this model is government guarantees, the difference represents the extra value that government guarantees provide to a bank's market value of equity. To summarise, the market value of equity should be higher for the riskier bank. Consequently, we expect a high MBV to lead to larger tail risk.

5 Hypothesis

5.1 Estimating tail risk

As previous research has focused on the relationship between government guarantees and model-free risk measures of banks in the US financial market, the goal of this thesis is to expand the analysis to European banks. A comparison will be drawn between a US and European data sample of banks, to see if there are signs of market participants pricing in government guarantees into the market value of equity in Europe as well.

Malik and Xu (2017) claim that the interconnectedness in the banking sector is mainly sourced from banks headquartered in the US and in Europe. Furthermore, Straetmans and Chaudhry (2015) show that US banks are more exposed to both tail- and systemic risk. These findings imply that MBV and tail risk should have a positive relationship in Europe but play a more significant role in the US financial market. This leads us to our first two hypotheses:

H 1:1: There is a negative relationship between the MBV before the crisis and returns on bad days for European banks.

H 1:2: There is a weaker negative relationship in European banks, compared to US banks, between the MBV before the crisis and returns on bad days.

What is important to note is that a negative relationship with return on bad days is equivalent to a positive relationship with tail risk. Thus, in this thesis, these relationships will be used interchangeably when analysing our results.

Besides from the relationship between MBV and tail risk proposed by Meier and Meng (2018), other model-free approaches of measuring tail risk will be examined. We acknowledge that MBV is the product of P/E and ROE (Penman, 1996). As previous research has concluded that the relationship between MBV and tail risk exists, we expect a corresponding relationship between ROE and P/E against tail risk. Meiselman et al. (2018) suggest a strong positive relationship between ROE and tail risk, arguing that if banks were viewed as a portfolio of assets, risky assets will have higher return during normal times. Thus, the following two hypotheses are concluded for ROE and P/E.

H 1:3: There is a negative relationship between ROE before the crisis and returns on bad days for European banks.

H 1:4: There is a negative relationship between P/E before the crisis and returns on bad days for European banks.

Further, Meiselman et al. (2018) argue that ROE is a better approximation of risk than ROA, as risk is amplified by leverage and that ROA does not reflect the leverage of the bank. Therefore, we expect the following as our fifth hypothesis:

H 1:5: There is a weaker relationship between ROA and return on bad days compared to the relationship between ROE and return on bad days for European banks.

5.2 Explaining the market-to-book value

The second part of this thesis aims to examine the cause of the variation of the MBV during "normal" times and whether it is due to high performance or government guarantees. From our theoretical model, it can be concluded that the increased risk-taking by banks, as a result from government guarantees, leads to excess value to equity holders. Accordingly, government guarantees lead to an increased market value of equity. The government guarantees will be proxied by the derivation of Schweikhard and Tsesmelidakis (2011) presented in Section 3.2.3.

H 2:1: There is a positive relationship between a bank's MBV and government guarantees

We want to distinguish between banks efficiency and their risk-taking behaviour. Thus, the performance factor will be proxied by ROA. As it is believed that well-managed, efficient banks are valued higher by market participants, the market value of equity should increase with ROA. This leads us to the hypothesis:

H 2:2: There is a positive relationship between a bank's MBV and ROA

6 Data collection and methodology

6.1 Data collection

6.1.1 Estimating tail risk

Data collection and sources

The dataset in this study includes stock data for European and US banks. A European country is defined as one that is a member of the EU or a member of the Schengen border-free area as of January 2019 (The European Union, 2019). The crisis period is defined as the year 2007, since this is when the crisis is argued to have started (Rayner, 2008). Additionally, the pre-crisis period refers to the year 2006, as this is the peak of the US housing bubble and is believed to be a good representation of the market before the financial crisis hit.

In order to be considered as "banks" in the data sample, two criteria need to be fulfilled: (1) the company falls within the Standard Industrial Classification (SIC) codes 6020, 6021, 6022, 6029, 6035 and 6036, and (2) the company is included in the Global Industry Classification (GIC) codes 401010 and 401020. Subsequently, the resulting data sample is an unbalanced data panel of 132 and 429 different types of commercial banks and savings institutions in Europe and the US respectively – which we will refer to as "banks" in the rest of this thesis. It is important to note that Meier and Meng (2018) only defined banks through the SIC codes 6020, 6021, 6022, 6029, 6035 and 6036. However, when replicating their main regression with our definition of "banks" we obtained similar results, so the overall conclusions remain the same for the US financial market.

The fundamentals and securities data are gathered from the Wharton Research Data Services (WRDS) database. For the European banks, the fundamentals and securities data were gathered from Compustat - Global. For the US, CRSP/Compustat Merged - Banks was used for the annual fundamentals and Centre of Research in Security Prices (CRSP) for the securities data. The fundamentals data is collected on an annual basis, but quarterly data is used in case of missing values within the yearly data.

Currency transformation

Within the WRDS database, the European securities report their data in their domestic currencies. As a result, a currency translation was needed to make all values across countries comparable in USD. Each data point in the dataset is linked to a variable called curcdd (ISO Currency Code), which identifies the currency in which the data is reported in. The curcdd is then used to determine which exchange rate (exratd) should be used to convert the data from the domestic currency to GBP. Once this conversion has been done, all values are converted to USD with exratd. As the US banks already report their data in USD, no currency conversion is needed for the US data sample.

Tail risk

The tail risk serves as a proxy for the systemic risk of the individual banks during the crisis, which is based on the years 2007-2008 (Meiselman et al., 2018). As mentioned in the theory, MES lacks the ability to successfully measure tail risk ex-ante, which is why we are using the MES-method to calculate the actual tail returns during the crisis period (ex-post). The tail risk is referred to as "bad bank days" or "5% worst days". The bad days are defined as the days between 01/07/1926 – 31/12/2014 that the Fama and French 48 Industry portfolio (industry 44 of 48 for banks) experienced its 5% lowest value-weighted returns. The tail risk for each bank is then computed by taking the average returns that the bank experienced on these "bad days" (Meiselman et al., 2018; Meier and Meng, 2018).

Stock returns are use due to them being a better indicator of the realized risk in a bad tail event, in comparison to accounting profitability. Losses are not reported directly in the financial accounts but experience a slight delay and does therefore not represent the direct impact that a crisis has on a bank's risk. Contrary, stock returns capture the risk exposure immediately, as prices react instantaneously to unexpected news in the market (Meiselman et al., 2018).

Variables of interest

The independent variables in the main regression will be based on the pre-crisis period in 2006 (Meiselman et al., 2018). The construction of the ratios used in the regressions are presented on the following page.

$$MBV = \frac{Market\ capitalization}{Book\ value\ of\ tangible\ equity} \qquad ROE = \frac{Net\ income}{Book\ value\ of\ tangible\ equity}$$

$$ROA = \frac{EBIE}{Book\ value\ of\ total\ assets} \qquad P/E = \frac{Market\ capitalization}{Net\ income}$$

The MBV is obtained by dividing a company's market capitalization by its book value of tangible equity, where the market capitalization is the product of the closing daily share price and the number of shares outstanding at the end of the year. Tangible equity is used as it represents the amount of losses that the bank can withstand before shareholder equity falls to zero. When tangible equity was missing, we calculated the measure through the equations:

$$Tangible\ equity$$
$$= stockholder\ equity - preferred/preference\ stock - intangible\ assets$$
$$= common/ordinary\ equity - intangible\ assets$$
$$= total\ assets - total\ liabilities - preferred/preference\ stock - intangible\ assets$$

ROE is defined as net income divided by the book value of tangible equity. Tangible equity is again used here due to the reasons explained above. Additionally, ROE is assumed to be closely related to the residual claim that equity holder received after government guarantees presented in our theoretical model (Section 4.3.2). The profitability measure ROA is measured as EBIE over the book value of total assets and the P/E ratio is defined as the market capitalization of the bank over its net income. See Appendix 5 for a more detailed definition of the variables used in the thesis.

6.1.2 Explaining the market-to-book value

Data collection and sources

The sample used in this part of the thesis includes data from 229 US banks gathered from the WRDS Compustat/CRSP merged dataset for North American banks, covering the years 2001-2017. All of the data used is gathered from WRDS database, whereby the option data has been collected from OptionMetrics Volatility Surface and the CDS spreads are collected from Markit -

Credit Default Swap. Based on the companies included in the Markit and OptionMetrics database, information on stock prices and annual report data was retrieved through the CRSP/Compustat database. Treasury rates was collected from the Interest Rate data included within the Federal Reserve Bank Reports database. The data ranges between 2001 and 2017, but only includes non-crisis periods.

Variables of interest

The theory behind the GG estimate can be found in Section 3.2.3, whilst the actual calculation is presented in Section 6.2.2. The construction of the variables MBV and ROA remain the same as the first part of the thesis:

$$MBV = \frac{Market\ capitalization}{Book\ value\ of\ tangible\ equity} \qquad ROA = \frac{EBIE}{Book\ value\ of\ total\ assets}$$

As a second step, the components of the GG estimate, namely the CDS spread and c, as well as P(t) and G(t+ξ) is used in a separate regression, where CDS spreads are represented by the average 5-year CDS spread calculated on a quarterly basis for each individual firm and c, P(t) and G(t+ξ) is calculated using the methodology in Section 6.2.2.

6.2 Methodology

6.2.1 Estimating tail risk

Primary regression

The first research question aims to analyse if government guarantees can serve as a risk factor by looking at the relationship between a bank's MBV and its tail risk. This study uses log-log regressions when analysing tail risk, whilst Meier and Meng (2018) uses level regressions. Thus, in order to make a US and European comparison, the first step is to replicate Meier and Meng's (2018) study and produce a log-log regression with the replicated data. All regressions also include robust standard errors to control for heteroskedasticity.

The next step involves looking at the explanatory power of MBV, ROA, ROE and P/E with regards to tail risk. The main focus is the MBV, but the ROA, ROE and P/E variables are included

to see if there are any distinct differences with the US data that can help us better explain tail risk in Europe.

$$Return_i^{crisis} = \beta_0 + \sum \beta_J \times X_i^{pre-crisis}$$

where Return is the "bad bank day" return for the respective bank, which represents the bank's tail risk. "Bad bank days" are the 5% worst performing days of the Fama and French banking industry portfolio from July 1926 to December 2014, also referred to as crisis returns in the study. The X represents the variables of interest – MBV, ROA, ROE and P/E.

In order to eliminate outliers, ROE values below 1% and negative P/E ratios are dropped from the data sample. Additionally, since the pre-crisis period is supposed to reflect "normal" times, observations with MBV values below 0.5 are dropped. MBV values below 0.5 are believed to be an indication of a bank being in distress (International Monetary Fund, 2013) and would therefore not reflect "normal" operations. Finally, any missing values within the main variables used – tail risk, MBV, ROE, ROA and P/E – are dropped in order to keep the number of observations consistent within the main regression.

Control Variables

In order to validate our findings, control variables are added to see if the explanatory power of the MBV is correlated with the following factors: size, book leverage, market leverage, non-interest income, interest income, intangible assets, loans, deposits and dividends. A more detailed description of the variables and how they are constructed can be found is Appendix 5.

$$Return_i^{crisis} = \beta_0 + \beta_1 \times MBV_i^{pre-crisis} + \sum \beta_J \times Control_i^{pre-crisis}$$

Size. Bostandzic et al. (2018) argue that the main drivers of financial fragility include size, interconnectedness and the quality of its loan portfolio. Additionally, Malik and Xu (2017) claim that interconnectedness in the banking sector is mainly sourced from banks headquartered in the US and in Europe. Considering the TBTF phenomenon, larger banks are assumed to have a more important role in the financial market. Larger banks are also assumed to have a greater interconnectedness with the rest of the financial system, leading to greater systemic risk and thus

a greater chance of receiving government guarantees. As a result, a negative relationship is predicted between size and returns – reflecting a positive relationship between size and tail risk.

Leverage. Book leverage is calculated as the sum of liabilities divided by the sum of total assets. Market leverage is defined as the sum of the book value of liabilities divided by the sum of the market value of total assets. The market value of total assets is calculated as the sum of the book value of liabilities and the market value of equity (Atkeson et al., 2018). Even though the two measurements of leverage are closely related, there is a divergence of the two values over time. Ferris et al. (2018) find that the book leverage is only adjusted when the change in market leverage is due to an increase in equity values. The increase in equity value comes from growth opportunities, but when the growth is not accompanied by an increase in assets, the amount of leverage needs to decrease in order to make the total assets balance with the sum of total equity and liabilities. As a result, the book leverage is greater than the market leverage of the firm. We aim to measure the impact that both measures of leverage have as a control variable in our regression. Government guarantees lead to a reduced cost of debt, thus encouraging banks to take on more leverage and take more risk. Consequently, a positive relationship between leverage and tail risk is expected.

Non-interest- and interest income. Non-interest income is the revenue obtained from fees and other activities that are outside the core lending business of the bank. Interest income, on the other hand, comes from the main deposit- and lending activities of the firm. It is proven that banks with a higher share of profits from non-interest income have a greater contribution to systemic risk (Meiselmanet al., 2018). Thus, we expect a negative correlation for both variables, but that non-interest income has a higher significance.

Intangible assets. Intangible assets are non-physical and include factors such as brand-recognition, patents and goodwill. Thus, by including intangible assets in the regression we are able to analyse the amount of increased equity value that may be due to government guarantees and which portion is due to intangible assets. Investments in intangible assets pose both risks and benefits for banks, and the risk lies in the probability of the investment yielding the anticipated returns (Chen and Danbolt , 2014; Ozili, 2019).

Loans and deposits. A systemic crisis affects the whole economy and thus the risk of multiple firms defaulting on their bank loans increases. This causes banks to reduce their exposure to loans through credit shortening (Alexandre et al., 2018)**.** Regarding deposits, previous research has found a negative relationship between a strong deposit base and bank risk (Altunbas et al., 2011). Consequently, we assume a positive correlation between loans and tail risk and a negative relationship for deposits.

Dividends. Dividends is defined as the total amount of dividends declared on the common/ordinary capital of a company, due to common equity best reflecting the idea of market-based capital requirements (Acharya et al., 2009). It has been argued that higher dividend payout results in higher systematic tail risk (Meiselman et al., 2018). During the crisis, some banks are seen to have paid out dividend despite having liquidity issues, which violates the priority of debt over equity and reduces the common equity base (Acharya et al., 2009). The resulting risk-shifting behaviour of banks may lead to increased systemic risk due to the interconnectedness of the financial system.

Beta. The beta measures the systematic risk of individual stocks. Nijskens and Wagnerb (2011) found that an increased beta is driven by higher correlations between banks, rather than an increased volatility. Additionally, market participants are believed to have been aware of this increased systemic risk since the beta of individual banks are seen to increase prior to the crisis. Subsequently, the beta is an important factor to consider when measuring the tail risk of individual banks. As this study is a comparison between US and European banks, the MSCI World Index is used to calculate the beta, to reflect the global market.

6.2.2 Explaining the market-to-book value

Primary regression

The second part of the thesis aims to expand on the results obtained in the first part of the thesis for US banks. We will explore how much of the variation in non-crisis MBV can be explained through government guarantees and how much is due to performance quality. However,

determining when a crisis starts and ends is a rather subjective task. Thus, we have based our definition of the "non-crisis" periods through the use of three crises: the internet bubble, the financial crisis and the sovereign debt crisis. We have used external sources to determine which years these crises occurred and excluded these from our dataset, resulting in the non-crisis periods: 2001-2003, 2004-2006 and 2015-2017. The first period (2001-2003) is chosen as it occurs after the internet bubble in 2000 (Morris and Alam, 2012). The second period (2004-2006) reflects the pre-crisis period of the 2008 financial crisis. The motivation as to why 2006 is the year used for the pre-crisis period remains the same as in the first part of the thesis. The third period (2015-2017) has been chosen as it aims to capture the MBV after the sovereign debt crisis in Europe, which is argued to have had its peak in mid-2014 (Praet, 2017). The time periods are two years long, starting with Q4 of the first year as t=0. All of the regressions in this section will be log-log to incorporate nonlinearities in our variables, as well as including robust standard errors to control for heteroskedasticity. The main regression used to analyse the variation in the MBV is presented as:

$$MBV_{i,t} = \beta_0 + \beta_1 \times GG_{i,t} + \beta_2 \times ROA_{i,t}$$

where t denotes quarterly time periods, expressed in annual terms. The construction of MBV is the same as described in Section 6.1.1.

ROA is used as a proxy for performance quality. The construction of this variable remains the same as in Section 6.1.1. The GG estimate is calculated using the CreditGrades methodology followed in Schweikhard and Tsesmelidakis (2011), presented in Section 3.2.3. We calculate the premium c of a CDS with maturity T using at-the-money put options with the following equations:

$$c = r(1-R)\frac{1 - P(0) + e^{r\xi}G(t+\xi) - G(\xi))}{P(0) - P(t)e^{-rt} - e^{r\xi}G(t+\xi) - G(\xi))}$$

where:

$$P(t) = \Phi\left(-\frac{A_t}{2} + \frac{\log(d)}{A_t}\right) - d \times \Phi\left(-\frac{A_t}{2} - \frac{\log(d)}{A_t}\right),$$

$$d = \frac{S_0 + \bar{L}D}{\bar{L}D} exp\lambda^2,$$

$$A_t = \sigma_V^2 t + \lambda^2,$$

$$\sigma_V = \sigma_S \frac{S}{S+\bar{L}D},$$

$$\xi = \frac{\lambda^2}{\sigma^2},$$

$$G(u) = d^{z+\frac{1}{2}}\Phi\left(-\frac{\log(d)}{\sigma_V\sqrt{u}} - z\sigma_V\sqrt{u}\right) + d^{-z+\frac{1}{2}}\Phi\left(-\frac{\log(d)}{\sigma_V\sqrt{u}} + z\sigma_V\sqrt{u}\right),$$

and

$$z = \sqrt{\frac{1}{4} + \frac{2r}{\sigma_V^2}}$$

In order to calculate c, certain assumptions have been made:

- The standard deviation of L, λ, is set to 0.3 (Finger et al., 2002)
- The recovery rate R is set to 0.5 (Yu, 2006)
- The risk-free interest rate r is assumed to be the US Treasury, five-year constant maturity rate (Schweikhard and Tsesmelidakis, 2011)
- $\bar{L}$ is assumed to be 0.225 (Schweikhard and Tsesmelidakis, 2011)
- t = 0 is set at Q4 of the first year in the time period
- t represents the distance in annual terms from our t (0). Hence, for example Q2 2005 is represented as t=1.5.
- σ^{equity} is represented by the implied volatility derived from ATM put options for each respective stock at time t
- S is the stock price for each respective stock at time t

The value of the GG estimate is calculated as the difference between the implied CDS spread c and the actual CDS spread.

$$GG_{i,t} = c_{i,t} - CDS\ spread_{i,t}$$

where CDS spread is the average spread on a quarterly basis for each individual firm in the dataset. We will use two GG estimates. One where using the actual 1-year CDS spread (GG 1Y) and one using the actual 5-year CDS spread (GG 5Y).

Decomposition analysis

In the regression model, the GG estimate constitutes of two subcomponents – the actual CDS spread and the implied CDS spread (c). It is possible that one of the components of our GG estimate is the underlying explanatory factor of the MBV, and that the other parts of the model add noise to our regression. If so, a "cleaner" estimate could be used to explain the MBV without compromising the explanatory value. The GG decomposition analysis will be twofold. Firstly, the GG estimate components (CDS and c) will be tested against the MBV to determine whether both subcomponents add value to model, or if one of them can be excluded. Secondly, the subcomponents of c will be analysed. The CreditGrades model consists of constant variables, which we have assumed to take on a specific value, and non-constant variables that differ for each observation. The main non-constant components in the calculation of c are P(t) and G(t+ξ). Thus, P(t) and G(t+ξ) will be extracted from the CreditGrades model and regressed against the MBV to evaluate their individual explanatory power.

$$MBV_i^t = \beta_0 + \sum \beta_J \times X_i^t$$

where X represents the different decomposed variables tested against the MBV. Thereafter, the most relevant decomposition is regressed with the GG estimate to analyse whether any of the decomposed variables has a better explanatory power than the GG estimate. If so, this would be indicative that it would be preferable to use this variable directly, instead of the GG estimate, to avoid noise in the independent variables.

Robustness tests

To ensure the robustness of our findings, we will control whether our results remain significant across firms and over time. Company fixed effects are used to analyse whether our results are valid for all firms, or if the model is driven by individual companies or a subgroup of firms. To verify

our findings over time we incorporate fixed effects on an annual level. The company- and time fixed effects are analysed with respect to the full data sample, including all three time periods (2001-2003, 2004-2006, 2015-2017). Thereafter, to further investigate the robustness of our results with respect to time, we run regressions on all three time periods separately, excluding time fixed effects. Time fixed effects are not included since the separate regressions indirectly control for time.

7 Estimating tail risk

7.1 Descriptive statistics

The first part of the thesis aims to explain tail risk using the variables MBV, ROA, ROE and the P/E ratio. The summary statistics for the replicated US data, based on the study by Meier and Meng (2018), is shown in Table 1b.

Table 1. Summary statistics
This table reports the summary statistics for the key variables used in our analysis. The results for the European banks are shown in Table 1a and the replicated results for the US banks are in Table 1b. "Bad bank days" are the 5% worst performing days of the Fama & French banking industry portfolio from July 1926 to December 2014. The construction of these variables is reported in Appendix 5.

Table 1a – European banks

Variable	Obs	Mean	Std. Dev.	Min	Max
Return on bad bank days (%)	132	-0.82	0.98	-2.83	2.93
Tangible Equity (billions)	132	1.48	2.79	0.01	18.54
Assets (billions)	132	50.21	108.58	0.05	509.24
ROA (%)	132	3.71	1.21	1.92	12.78
ROE (%)	132	17.96	8.18	3.09	49.39
Market-to-book value	132	2.63	1.24	0.64	9.65
Price-earnings ratio	132	17.09	17.23	4.29	197.71

Table 1b – US banks

Variable	Obs	Mean	Std. Dev.	Min	Max
Return on bad bank days (%)	429	-2.09	1.76	-7.70	0.99
Tangible Equity (billions)	429	0.77	4.23	0.01	55.75
Assets (billions)	429	16.29	106.90	0.10	1459.74
ROA (%)	429	4.08	0.77	2.02	7.93
ROE (%)	429	13.70	7.69	1.13	78.68
Market-to-book value	429	2.38	0.96	0.81	8.84
Price-earnings ratio	429	21.68	15.36	4.84	129.50

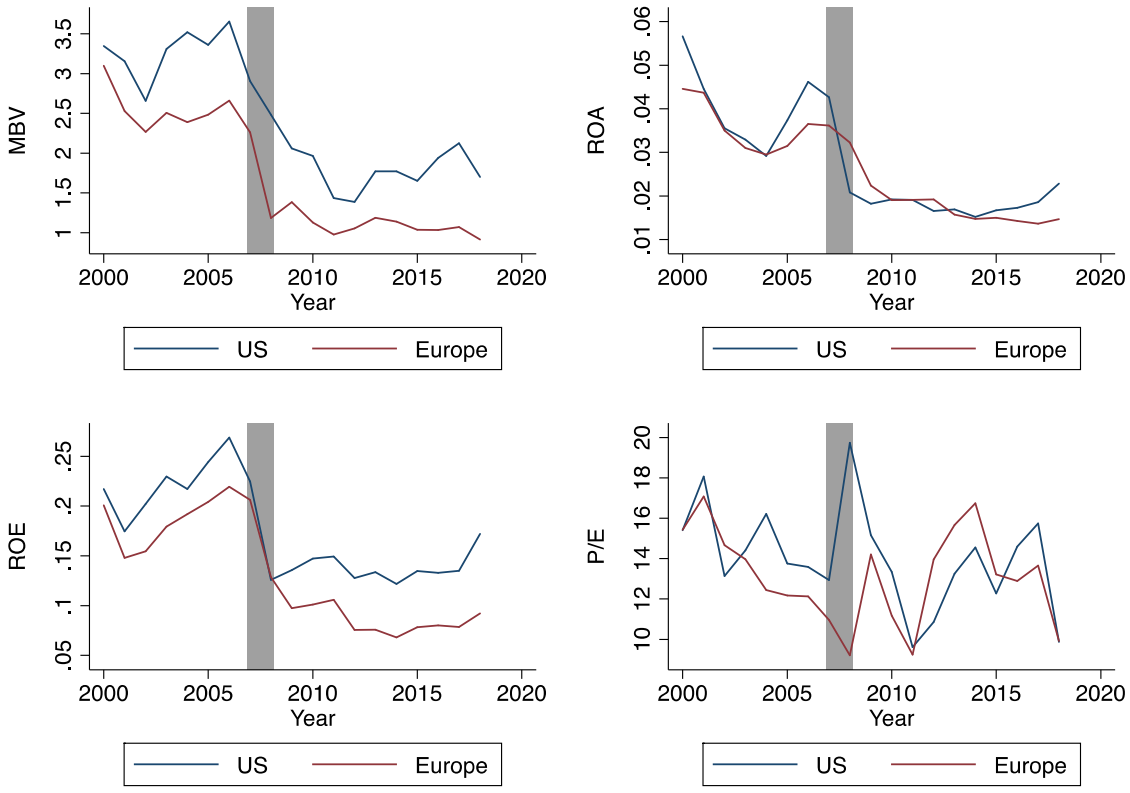
After dropping outliers (see Section 6.2.1), the European sample results in 132 banks in 28 countries and the replicated US data contains 429 observations. Within the data samples, we have banks with total assets ranging from $0.05 – $509,24 billion in Europe and $0.10 – $1,459.74 billion in the US, indicating that the larger banks can be found in the US sample. However, the mean asset value is higher for the European sample, denoting that the average European bank is larger. Additionally, the European banks are seen to have a higher maximum ROA, but a smaller ROE and amount of tangible equity. The MBV and P/E ratio in Europe are seen to have a higher

maximum value of 9.65 and 197.71 respectively, compared to 8.84 and 129.50 in the US. A higher MBV entails that there are intangible qualities that are valued highly by investors, causing the market value of equity to increase with respect to the book value of equity. Thus, the results imply that investors value the intangible qualities in European banks higher than in US banks, or that there are more intangible qualities present in European banks. With the help of our theoretical model, we aim to clarify if the higher MBV for European banks are due to government guarantees or due to other external factors. Finally, the US banks are seen to be more volatile with respect to their crisis returns, having a minimum return of -7.70%, compared to -2.09% in European banks, implying that US banks suffered more from the crisis.

The diagrams below show the evolution of the variables of interest over time for European and US banks.

Figure 1. Variables of interest over time

This figure presents the historical development of the variables of interest over time, where the variables of interest include the market-to-book value (MBV), the return on assets (ROA), the return on equity (ROE) and the price-earnings ratio (P/E). The shaded region represents the crisis period of 2007-2008.



Similar trends are seen across the two regions, with US banks experiencing higher ratios in most time periods. For the US sample, the profitability ratios (ROA and ROE) and the P/E ratio are seen to be more impacted from the crisis than the MBV. The European banks see a sharper decrease in the MBV during the crisis period in comparison to the US banks, but a more stable evolution of the ROA. Both ROE and ROA are profitability ratios, but whilst the European ROA experiences a smoother decline during the crisis, the ROE experiences a sharp decrease. However, as ROA has been argued to reflect performance quality (Section 6.2.2), the figures could suggest that the crisis impacted profitability on earnings more than the efficiency in operations in European banks. The evolution of the P/E ratio over the crisis is interesting as the change in value across the two regions contradict each other, with the US banks experiencing an increased P/E ratio and the European banks a decreasing value. There seems to exist some time-lagged effect of the European P/E ratio, as the ratio sharply rises again in 2009.

7.2 Results

7.2.1 Main regression

The main regression (Table 2) analyses the relationship between tail risk and the independent variables MBV, ROA, ROE and P/E. The results in Europe follow a similar pattern to the ones seen in the US sample, but the R^2 in the European regression is often half the size of the R^2 in the US. To clarify the comparison between the European and US data sample, the results obtained for the US banks will be stated in squared brackets. The MBV alone is seen to produce an adjusted R^2 of 15.8% [32.8%] and a t-statistic of -4.224 [-14.05]. The significant negative coefficient for the MBV mirrors the findings in Meier and Meng (2018) and leads to the acceptance of H1:1[2]. The results suggest that a 1% increase in the MBV will result in a 0.00876% [0.0286%] decrease in returns, thus an increase in tail risk. The small size of the coefficients indicates that there are other factors driving tail risk during the 2008 crisis, and more so in European banks. With references to our theoretical model, the positive relationship between MBV and tail risk could be indicative of government guarantees being priced into the market value of equity of European banks. Additionally, the MBV coefficient for European banks is seen to be smaller and less significant

[2] H 1:1: There is a negative relationship between the MBV before the crisis and returns on bad days for European banks

than the US, resulting in the acceptance of H1:2[3]. Even though the MBV coefficient in regression 2:1 and A2:1 (Appendix 2) are significant at the 1% level, the lower t-statistic in European banks causes the MBV to only be significant on the 5% level when adding ROE to the regression, whilst the US remains at the 1% significance level. However, the ROE and P/E metrics do not show any significances when combined with the MBV in the US sample – regressions A2:5 and A2:7 – but there is a 5% significance for both variables for European banks. This implies that the ROE and P/E ratios add more explanatory value to tail risk in European banks, whereas for the US banks, MBV captures all the relevant information. One explanation to this could be the mixed regulatory and accounting standards within Europe, which causes the MBV to not reflect consistent definitions across firms. Thus, investors look at "cleaner" metrics, such as the ROE and P/E.

Table 2. Main regression – European banks
This table reports the results from the main OLS regression, which analyses the relationship between tail risk and the market-to-book value (MBV), return on assets (ROA), return on equity (ROE) and price-earnings ratio (P/E).

$$Return_i^{crisis} = \beta_0 + \sum \beta_J \times X_i^{pre-crisis}$$

where Return is the "bad bank day" return for the respective bank, representing the tail risk, and X represents the variables of interest. All variables are in natural logarithm. The results for the replicated US banks can be found in Appendix 2.

	(2:1)	(2:2)	(2:3)	(2:4)	(2:5)	(2:6)	(2:7)
MBV	-0.00876***		-0.00875***		-0.00624**		-0.0101***
	(-4.224)		(-4.184)		(-2.763)		(-4.197)
ROA		-0.000997	-0.000561				
		(-0.289)	(-0.200)				
ROE				-0.00642***	-0.00384**		
				(-3.731)	(-2.498)		
P/E						0.00112	0.00384**
						(0.570)	(2.498)
Constant	-0.000680	-0.0116	-0.00256	-0.0200***	-0.00988**	-0.0113**	-0.00988**
	(-0.376)	(-1.012)	(-0.272)	(-6.379)	(-2.601)	(-2.143)	(-2.601)
Observations	132	132	132	132	132	132	132
R^2	0.164	0.001	0.164	0.140	0.201	0.003	0.201
Adjusted R^2	0.158	-0.00680	0.151	0.133	0.188	-0.00426	0.188
Countries	28	28	28	28	28	28	28
Country FE	YES	YES	YES	YES	YES	YES	YES

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[3] H 1:2: There is a weaker negative relationship in European banks, compared to US banks, between the MBV before the crisis and returns on bad days.

Both regression 2:5 and 2:7 result in a 18.8% adjusted R^2, but the t-statistic for the MBV remains around -4 when adding the P/E ratio to the model and drops to -2.763 when combined with ROE. This denotes that both regression models explain the same variation in tail risk, but that the combination of MBV and P/E more significantly explains the amount of tail risk experienced by banks during the 2008 crisis. The results indicate that a higher ROE leads to high tail risk and thus the acceptance of H 1:3[4]. However, a higher P/E ratio results in lower tail risk, which leads to the rejection of H 1:4[5]. The ROA lacks significance in the European data sample, causing the acceptance of H1:5[6] to be ambiguous. This contrasts with the US findings that indicate a significant positive relationship with tail risk, which suggests that ROA carries more information about tail risk in the US market. The reason for this can be driven by external factors such as different accounting standards, regulatory frameworks and investors' behaviour.

7.2.2 Robustness tests

The main regression concluded that the MBV can significantly explain tail risk, where a higher MBV leads to lower bad day returns. This section aims to test the validity of our findings under different assumptions. We will first check the robustness of our results by adding individual control variables to the MBV regression and then we will test a selected number of control variables together to evaluate the optimal model for tail risk with the variables in the study.

Appendix 3 shows how the explanatory power of MBV varies when controlled for several different factors[7]. The MBV coefficient is seen to be significantly negative in all regressions, highlighting that the results of the MBV being positively correlated with tail risk is robust. When controlling for size, the regression produces an adjusted R^2 of 46.4%, with size being significant on the 1% level but with the MBV at 10%. The significant negative relationship of the Size coefficient confirms that firm size is a big driver of tail risk – mirroring the TBTF phenomenon and reflecting previous studies (Meier and Meng, 2018; Bostandzic and Weiß, 2018). Additionally, as Size has a greater significance than the MBV, it entails that firm size contains more information about tail risk that is not captured by MBV alone. Other control variables that are seen to be

[4] H 1:3: There is a negative relationship between ROE before the crisis and returns on bad days for European banks.
[5] H 1:4: There is a negative relationship between P/E before the crisis and returns on bad days for European banks.
[6] H 1:5: There is a weaker relationship between ROA and return on bad days compared to the relationship between ROE and return on bad days for European banks.
[7] The control factors include size, leverage, income, tangible assets, loans, deposits, dividends and beta

significant on the 1% level are intangible assets and deposits, which increases the adjusted R^2 of the main regression (15.8%) to 23.6% and 26% respectively. The coefficients suggest that firms with more intangible assets and less deposits have a significantly higher tail risk. An explanation to the results could be that firms with more intangible assets often have fewer liquid assets that can be sold to generate cash. Additionally, deposits are known to be a stable funding source, compared to for example interbank lending that may become scarce and expensive during crisis periods. Consequently, a bank with a low deposit ratio should have larger losses during a crisis, which is consistent with our findings.

Meiselman et al. (2018) state that non-interest income can help explain the variation of tail risk, which is in line with our findings. Furthermore, Meier and Meng (2018) argue that beta is a driver of tail risk, but we do not find a significant relationship in our US data sample. This could be due to our study using the MSCI World Index to proxy for the global market, whilst Meier and Meng (2018) use the value-weighted S&P 500 Index to proxy for the US financial market. We do however see a 10% significant negative relationship between tail risk and beta in the European sample. These results imply that European banks could be more exposed to global factors and that US banks are mainly driven by factors within the US market. Another unexpected finding is that book leverage is not seen to significantly affect tail risk in European banks and market leverage only has a 10% significance. Conversely, a 1% significance is seen in the US sample for both market- and book leverage. With reference to our theoretical model, government guarantees should lower the cost of debt and thus allow banks to increase debt financing, which consequently increases leverage. The results therefore signal that US companies took more advantage of the government guarantees by taking on more debt to finance riskier projects prior to the crisis.

The variables with the highest significances are further analysed in Table 3 in order to evaluate the optimal model for tail risk in European banks. When the selected control variables – size, non-interest income, intangible assets, deposits and beta – are tested in a variety of combinations, the MBV is always seen to have a significant and negative correlation with bad returns, suggesting that our findings in the main regression are robust. Furthermore, the optimal model for explaining tail risk is concluded to be when the MBV is controlled for Size, which denotes that increased bank size contributes the most to tail risk. Even though regression 3:5 and 3:9 lead to an adjusted R^2 of 47.2% and 46.4% respectively, they are not believed to be better models when it comes to explaining tail risk. In regression 3:5, intangible assets lose significance

while the t-statistics for MBV and Size remain similar to the ones seen in regression 3:1. Thus, regression 3:5 does not significantly add extra value. In regression 3:9 we see the same adjusted R^2 as in 3:1, indicating that the added beta to the model does not add more explanatory power in the variation of tail risk. Additionally, it is important to note that regression 3:5 has 124 observations and 3:1 and 3:9 have 132. When having the same observations in all regressions (124) the R^2 of 3:1 and 3:9 increase to 47.1% and 47% respectively (see Appendix 4).

The coefficients for intangible assets and deposits lose their significance when combined with MBV (3:5) and Size (3:7). This implies that Size at least includes all the information that is present in Intangible Assets and Deposits. The t-statistic for non-interest income does not change to a great extent when added with MBV and Size, but the R^2 value is smaller than the one seen in regression 3:1. However, when dropping the number of observations in regression 3:1 to match the companies in regression 3:3, we result in an adjusted R^2 of 37.4% in regression 3:1. Thus, non-interest income does add value to tail risk, which is in line with Meiselman et al. (2018) (See Appendix 4). The positive coefficient suggests that non-interest income helps a bank diversify the value generated from its operations and become less dependent on its core-banking activities, which subsequently reduces tail risk. However, it is unclear as to how much value-added regression 3:3 would provide if it included all the 132 companies seen in regression 3:1. Thus, we conclude that regression 3:1 is the most relevant model.

Table 3. Selected control variables

After having run the control variable regression (Appendix 3) we selected the control variables with the highest significance and tested them with each other. Therefore, this table reports the results from the OLS regression that estimates the relationship between the market-to-book value (MBV) and tail risk for European banks, with selected control variables with high significance. As Size was seen to be the most significant factor, with the highest R^2, it is the main control variable of interest in these regressions.

$$Return_i^{crisis} = \beta_0 + \beta_1 \times MBV_i^{pre-crisis} + \sum \beta_J \times Control_i^{pre-crisis}$$

where Return is the "bad bank day" return for the respective bank, representing the tail risk, and Control represents the control variables used with the MBV. All variables are in natural logarithm. The construction of these variables is provided in Appendix 5.

	(3:1)	(3:2)	(3:3)	(3:4)	(3:5)	(3:6)	(3:7)	(3:8)	(3:9)
MBV	-0.00419*	-0.00809***	-0.00505**	-0.00703***	-0.00407*	-0.00772***	-0.00416*	-0.00875***	-0.00420*
	(-1.913)	(-3.530)	(-2.385)	(-3.128)	(-1.768)	(-4.128)	(-1.824)	(-4.251)	(-1.929)
Size	-0.00251***		-0.00226***		-0.00243***		-0.00256***		-0.00250***
	(-7.420)		(-5.743)		(-8.128)		(-5.237)		(-7.379)
Non-Interest Income		0.00360**	0.00289**						
		(2.690)	(2.082)						
Intangible Assets				-0.00140***	-0.000378				
				(-2.903)	(-0.906)				
Deposits						0.00825***	-0.000395		
						(2.929)	(-0.145)		
Beta								-6.682*	-5.149*
								(-1.745)	(-2.048)
Constant	0.0173***	0.0160**	0.0289***	-0.0108**	0.0144***	0.00383	0.0174***	-0.000754	0.0172***
	(6.131)	(2.632)	(6.018)	(-2.473)	(2.949)	(1.348)	(6.089)	(-0.419)	(6.066)
Observations	132	105	105	124	124	132	132	132	132
R^2	0.472	0.235	0.442	0.249	0.485	0.272	0.473	0.171	0.476
Adjusted R^2	0.464	0.220	0.426	0.236	0.472	0.260	0.460	0.158	0.464
Countries	28	26	26	28	28	28	28	28	28
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

8 Explaining the market-to-book value

8.1 Descriptive statistics

Table 4. Summary statistics
This table reports the summary statistics for the key variables used in the main regression. The data sample only includes US banks. The construction of these variables is reported in Appendix 5, except for the government guarantee (GG) estimate and the implied CDS spread, which is presented in Section 6.2.2.

Variable	Obs	Mean	Std. Dev.	Min	Max
Market-to-book value	229	3.24	1.40	1.00	8.23
Tangible Equity (billions)	229	21.74	35.25	2.40	178.54
Total assets (billion)	229	368.12	522.44	14.05	2563.17
Government Guarantees, 5Y estimate (%)	229	-0.49	0.46	-2.88	1.50
Government Guarantees, 1Y estimate (%)	202	-0.25	0.36	-2.76	1.99
ROA (%)	229	1.45	0.84	0.31	4.41
CDS spread 5Y (%)	229	0.48	0.44	0.11	2.90
CDS spread 1Y (%)	202	0.24	0.31	0.03	2.78
Implied CDS spread (%)	229	-0.01	0.16	-0.11	2.21

The data sample contain 229 observations, with the exception of the 1-year CDS spread and government guarantee (GG) estimates that contain 202 observations. The sample contains banks with a total asset value ranging between $14.05 – $2,563 billion. Compared to the data sample in Part 1 (Estimating tail risk), it can be concluded that the average banks in this analysis are much larger and hold larger amounts of tangible equity. One possible explanation for this is that the data sample requires banks to trade stocks, options and CDS securities – implying that the bank has to be large enough to attract a substantial investor base. The sample size poses a limitation to our data that has to be kept in mind during the analysis. Even though this data sample contains larger banks, the descriptive statistics for the MBV remain similar to ones seen in Part 1 for the US sample. The GG estimates have negative values, with the minimum being -2.88% and -2.76% for the 5Y and 1Y GG estimates respectively. This is a consequence of our implicit CDS spreads being very low or negative. It can be argued that the model used to calculate the implicit CDS spreads is not able to incorporate certain characteristic that are drivers of CDS pricing, and hence estimates the spread to be too low. The idea of a negative GG value is counterintuitive as a negative government guarantee would imply that the bank would owe money to the state. Thus, we deem the negative GG estimates to be a shortcoming of the model. However, as the CreditGrades model is aimed to calculate the level of government guarantees that a bank could obtain in case of a crisis, we assume

that the GG estimate is able to reflect this level. Thus, to make the results more intuitive, the GG estimate is adjusted with a factor of 1+ to make all values positive. The smallest GG estimate then represents the firms with the lowest estimated government guarantees and the larger the GG estimate, the more potential guarantees a bank can obtain in case of a crisis.

8.2 Results

8.2.1 Main regression

The main regression analyses whether the MBV is driven by government guarantees or the bank's performance quality in the years leading up to the crisis.

Table 5. Main regression
This table reports the results from the main OLS regression, which analyses the relationship between the market-to-book value (MBV) and the Government Guarantee estimate (GG) on both a 5Y and 1Y basis, as well as the relationship between the MBV and the return on assets (ROA).

$$MBV_i^t = \beta_0 + \sum \beta_J \times X_i^t$$

where MBV is the market capitalisation divided by tangible book equity, and X represents the variables of interest. The OLS is estimated for each respective bank (i) on a quarterly basis (t). All variables are in natural logarithm.

	(5:1)	(5:2)	(5:3)	(5:4)	(5:5)
GG (5Y estimate)	40.51***			29.30***	
	(4.650)			(4.638)	
GG (1Y estimate)		18.82			21.77**
		(1.581)			(2.485)
ROA			0.410***	0.352***	0.454***
			(10.28)	(8.795)	(11.11)
Constant	1.285***	1.128***	2.889***	2.778***	3.148***
	(27.51)	(27.67)	(16.27)	(16.62)	(17.08)
Observations	229	202	229	229	202
R^2	0.190	0.023	0.314	0.408	0.375
Adjusted R^2	0.187	0.0180	0.311	0.402	0.368

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

From 5:1, we can see a significant positive relationship between MBV and the GG estimate based on the 5-year spreads (GG 5Y), allowing us to accept H 2:1[8]. The relationship suggests that a 1%

[8] H 2:1: There is a positive relationship between a bank's MBV and government guarantees

increase in the GG estimate results in a 40.51% increase in MBV. The 1Y estimate (GG 1Y) does not display any significance. As the GG estimates both aim to capture government guarantees, it does not add value to include them both in the analysis going forward. Previous research has used 5-year CDS contracts as they are more frequently traded and more liquid (Blanco et al., 2005 ; Schweikhard and Tsesmelidakis, 2011). This, together with the higher significance of the GG 5Y estimate, leads us to focus on the GG 5Y estimate in the rest of the analysis. The ROA is significant in the main regression, causing the acceptance of H2:2[9]. These results indicate that investors consider both quality and government guarantees in the valuation of equity. Additionally, when the GG estimate and the ROA variable are combined, the significance of the two remain at the 1% level. This implies that ROA and GG explain different variations in the MBV and are not correlated to capture the same variations. As this thesis aims to gain a greater understanding of government guarantees and their impact on investors' valuation of banks, we will continue with the GG estimate in the rest of the thesis. As ROA and GG do not show strong signs of being interrelated, it is possible to analyse the GG estimate separately.

8.2.2 Decomposition analysis

In this section, the results from our decomposition analyses are presented. The table below contains two decompositions: (1) the regressions of the partial components of the GG 5Y estimate against the MBV (6:2 - 6:4) and (2) a regression of the subcomponents of c against the MBV (6:5 - 6:7).

The highest t-statistic (-8.868) and adjusted R^2 (33.7%) is obtained in regression 6:2, which displays the relationship between actual CDS spreads and the MBV. As CDS spreads are considered a proxy for credit risk, this result imply that riskier banks are valued less by investors. This contradicts our theoretical model, which suggests that higher risk should lead to larger equity returns and thus a higher valuation. From regression 6:3, the c variable is seen to be significant on the 1% level, but with a lower t-statistic (-3.069) and adjusted R^2 (0.461%) compared to model with the CDS spread. When the two variables are combined (6:4), the significance of c drops to 5% and the adjusted R^2 is slightly lower than that of regression 6:2. Conclusively, the results argue that CDS is a better predictor of the MBV than c.

[9] H 2:2: There is a positive relationship between a bank's MBV and ROA

Table 6. Decomposed variable regression

This table reports the results from the OLS regression which aim to estimate the explanatory value of partial components of the variable identified as the most significant in the main regression, the 5-year government guarantee estimate. The base model represents the same regression shown in Main regression, 5:1 and is included to facilitate comparison.

$$MBV_i^t = \beta_0 + \sum \beta_J \times X_i^t$$

where MBV is the market capitalisation divided by tangible book equity, and X represents the decomposed variables, as described below. All variables are in natural logarithm.

P (t): The survival probability of the firm at time t

G(t+**ξ**): The discounted expected spread payments, given by the accumulated survival probability of a firm until time t

	Base model	Decomposition of GG			Decomposition of c		
	(6:1)	(6:2)	(6:3)	(6:4)	(6:5)	(6:6)	(6:7)
GG (5Y estimate)	40.51***						
	(4.650)						
CDS spread (5Y)		-0.348***		-0.346***			
		(-8.868)		(-8.685)			
c			-26.04***	-11.57**			
			(-3.069)	(-2.082)			
P (t)					0.281***		0.336***
					(7.291)		(6.533)
G(t+**ξ**)						-0.0206**	0.0144
						(-2.532)	(1.119)
Constant	1.285***	-0.875***	1.084***	-0.863***	1.139***	1.090***	1.147***
	(27.51)	(-3.777)	(38.44)	(-3.676)	(37.55)	(38.07)	(38.82)
Observations	229	229	229	229	229	229	229
R^2	0.190	0.340	0.009	0.342	0.074	0.015	0.079
Adjusted R^2	0.187	0.337	0.00461	0.336	0.0704	0.0105	0.0706

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The second decomposition ('Decomposition of c') displays significant coefficients but regressions 6:5-6:7 result in adjusted R^2 that are lower than the ones seen in the Base model (6:1) and 'Decomposition of the GG' (6:2 and 6:4). The separate components of c are shown to better explain the variation in the MBV than c alone – denoted by the higher R^2 ranging from 1.05%-7.06%, compared to 0.461% in regression 6:3. Thus, it is better to look at the subcomponents of c when wanting to explain the MBV, rather than c alone. Furthermore, the G(t+ξ) is not significant when combined with the P(t) variable, causing the validity of the combined model to be ambiguous.

From the results presented in Table 6, we conclude that the 'Decomposition of GG estimate' increases the explanatory power of the Base model. We explore this finding further

through a selected decomposition analysis (Table 7). The regression of the GG estimate presented in the main regression is included to facilitate comparison. The Base model (7:1) shows that the GG estimate is highly significant when explaining the MBV. However, when combined with CDS and thereafter with both CDS and c, the significance drops to 5% and 10% respectively. Additionally, the GG coefficient switches sign, causing the interpretation of the relationship between GG and MBV to be ambiguous. The CDS coefficient consistently shows a high significance, suggesting that the relationship between the CDS spread and the MBV is robust. Additionally, by looking at model 7:4, it can be seen that when c is combined with both the CDS spread and GG, it is no longer significant. As GG only consists of the CDS spread and c, these results indicate that the relationship between the GG estimate and the MBV is mainly driven by the CDS spread. We conclude that going forward, the relationship between MBV and the CDS spread should be further explored. However, we will continue to include the GG estimate in our regressions to make sure some unique explanatory value of the GG estimate is not lost in the analysis.

Table 7. Selected decomposition

After having run the Decomposition regression (Table 6) we selected the decomposition with the highest significance (the GG decomposition, CDS and c) and analyse it together with the GG estimate. Therefore, this table reports the results from the OLS regression that estimates the relationship between the GG 5Y estimate and MBV, controlling for CDS and c.

$$MBV_i^t = \beta_0 + \sum \beta_J \times X_i^t$$

where MBV is the market capitalisation divided by tangible book equity, and X represents the variables of interest. The OLS is estimated for each respective bank (i) on a quarterly basis (t). All variables are in natural logarithm.

	Base model			
	(7:1)	(7:2)	(7:3)	(7:4)
GG (5Y estimate)	40.51***		-17.80**	-24.31*
	(4.650)		(-2.053)	(-1.654)
CDS (5Y)		-0.348***	-0.445***	-0.483***
		(-8.868)	(-8.995)	(-5.894)
c				15.13
				(0.886)
Constant	1.285***	-0.875***	-1.506***	-1.752***
	(27.51)	(-3.777)	(-4.812)	(-3.313)
Observations	229	229	229	229
R^2	0.190	0.340	0.350	0.352
Adjusted R^2	0.187	0.337	0.345	0.343

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

8.2.3 Robustness tests

The previous regressions indicated that there is a relationship between MBV and the GG estimate, which is mainly driven by the CDS spread. These findings will now be tested when controlling for variations of individual firms and years, to ensure that the results are robust across firms and over time. The tables on the next page show the results of our company- and year fixed effects regressions, along with a time-varying analysis to further control for time period variations in our model.

The regressions 8:1 and 8:2 show a significant positive relationship for GG and a significant negative relationship for CDS, suggesting that the results are robust. The results imply that the relationships are present across all banks and that it is not driven by a smaller group or a specific firm in the dataset. However, the year fixed effects in 8:3 and 8:4 are seen to decrease the significance for both GG and CDS, along with a reduction in their adjusted R^2. This suggests that the significance and explanatory power of the models vary over time. An explanation to this could be new regulatory standards being introduced, investors' changing behaviour and investor trends altering over different time periods. We therefore continue the time-varying analysis in Table 9, where we examine the year fixed effects indirectly by dividing the regression into the three time periods in the dataset. The table indicates robust results during the periods 2004-2006 and 2015-2017. For the GG estimate we see that the period 2004-2006 (9:3) contains the highest significant relationship but decreases to 5% significance in 2015-2017. On the other hand, the CDS spread remains at a 1% significance in both periods, suggesting that the results are more robust for the CDS spread. However, it is important to note that the period 2015-2017 has fewer observations in comparison to 2004-2006, which might obscure the robustness of the results. We see large fluctuations in the GG coefficient, which doubles in size between the years 2004-2006 compared to 2015-2017, further emphasising the existence of differences across time periods.

Table 8. Fixed effects regression

This table reports the results from the OLS regression, which estimates the relationship between the market-to-book value (MBV) and the Government Guarantee estimate (GG) and CDS spreads, while incorporating company- and time fixed effects.

$$MBV_i^t = \beta_0 + \sum \beta_J \times X_i^t$$

where MBV is the market capitalisation divided by tangible book equity, and X represents the variables of interest. The OLS is estimated for each respective bank (i) on a quarterly basis (t). All variables are in natural logarithm.

	Company fixed effects		Time fixed effects	
	(8:1)	(8:2)	(8:3)	(8:4)
GG (5Y estimate)	37.05***		16.03*	
	(2.848)		(2.125)	
CDS (5Y)		-0.348***		-0.185**
		(-6.279)		(-2.869)
Constant	1.274***	-0.864**	1.168***	0.0474
	(19.42)	(-2.781)	(30.71)	(0.131)
Observations	254	254	254	254
R^2	0.202	0.511	0.045	0.076
Adjusted R^2	0.199	0.509	0.0409	0.0725
Companies	22	22		
Company FE	YES	YES	NO	NO
Number of years			6	6
Year FE	NO	NO	YES	YES

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9. Time-varying analysis

This table reports the results from the OLS regression analysing the relationship between the market-to-book value (MBV) and the 5Y Government Guarantee estimate and the CDS spread, over different time periods.

$$MBV_i^t = \beta_0 + \sum \beta_J \times X_i^t$$

where MBV is the market capitalisation divided by tangible book equity, and X represents the variables of interest. The OLS is estimated for each respective bank (i) on a quarterly basis (t). All variables are in natural logarithm.

	(2001-2003)		(2004-2006)		(2015-2017)	
	(1)	(2)	(3)	(4)	(5)	(6)
GG (5Y estimate)	-9.411		34.26***		17.73**	
	(-1.168)		(7.729)		(2.331)	
CDS (5Y)		0.0117		-0.277***		-0.288***
		(0.170)		(-6.162)		(-3.689)
Constant	1.171***	1.285***	1.375***	-0.435	0.721***	-0.823**
	(18.91)	(3.403)	(42.27)	(-1.598)	(10.49)	(-2.123)
Observations	83	83	109	109	62	62
R^2	0.009	0.000	0.144	0.192	0.148	0.265
Adjusted R^2	-0.00301	-0.0121	0.136	0.185	0.134	0.253

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

When contemplating the results from our regressions in Part 2, we conclude that the ROA and our GG estimate can significantly explain the variations in the MBV. It has also been uncovered that our GG estimate is mainly driven by the negative relationship between actual CDS spreads and the MBV, suggesting that risky banks are valued less by investors. When performing our robustness checks, we find a consistent relationship on the individual firm level but that the relationship alters over time. This denotes that our findings apply to banks in general but that changing investor behaviours causes the results to not be a good representation for all time periods.

9 Conclusion

9.1 Discussion

In previous research it has been shown that the MBV can predict the tail risk of US banks during the 2008 financial crisis. The theoretical framework underlying these results imply that government guarantees were anticipated by investors prior to the 2008 crisis. This study has extended the analysis to Europe and finds that the MBV is significant in explaining tail risk in European banks, but that the relationship is more pronounced in the US financial sector. We also find evidence of ROE being a more effective predictor of tail risk in European banks, which is not clearly visible in the US, suggesting that investors tend to focus on "cleaner" ratios when valuing European banks. We have attributed this difference to the various reporting standards used throughout Europe, which might result in a lack of consistency in the construction of the MBV across banks. Our results also indicate that other bank characteristics are important to consider when evaluating tail risk – such as the size of the bank. We suggest that the reason for this is the likelihood of government guarantees taking place, with certain banks being more systemically important than others. Finally, we find that a bank's non-interest income adds value when trying to explain its MBV, which we attribute to the benefits of diversification.

In the second part of this thesis, we examine whether the variation of MBV in the pre-crisis period is due to performance quality or anticipated government guarantees. We find a significant relationship for both our performance quality and our government guarantee proxy – whereby the positive relationship between the MBV and the GG estimate is argued to be driven by the CDS spread component of the GG estimate. The implied CDS spread calculated using the CreditGrades framework is believed to mainly add noise to the model, causing the actual CDS spread to be a better predictor of the MBV. The actual CDS spread and the MBV has a highly significant negative relationship, denoting that higher risk should lead to a lower equity valuation. We also conclude that our findings are robust when controlling for variance across individual banks, but less so when controlling for time fixed effects. The results suggest that investor perceptions vary over time and had a greater impact on investment decisions prior to the 2008 crisis.

9.2 Limitations

As with all studies, this thesis contains limitations that can affect the concluding results. Firstly, both tail risk and government guarantees are difficult to directly measure. We have used "bad bank day" crisis returns to act as a proxy for tail risk, and the CreditGrades model for our GG estimate. As proxies involve certain assumptions and estimations, they will never be a true reflection of the factor of interest. The validity of our proxies therefore depend on the reliability of the MES calculation of tail risk and of the CreditGrades methodology when calculating the implied CDS spread. Adding to the estimation issues, our research contains a limited amount of available data. There is seen to be a smaller number of traded banks in Europe compared to the US data, which could affect the robustness of our results. Additionally, only the larger banks in the US sample are seen to contain information on CDS spreads and options, which can cause our results to be biased towards larger banks in the second part of the thesis. Consequently, this raises the question whether our findings are valid for US banks in general, or only for large ones.

An additional limitation is that our theoretical model only assumes one market imperfection, namely government guarantees. Realistically, there are numerous intangible factors that can affect the MBV, which are not captured or distinguished in the theoretical model. We have taken this into consideration in the interpretation of our results, but we have not modelled or estimated these imperfections directly. Finally, the first part of this thesis focuses on the financial crisis in 2008 and every crisis has its unique characteristics. The robustness checks in Part 2 suggest that investor perceptions can change over time, implying that the results obtained from Part 1 might not hold true for other crisis periods.

9.3 Future research

As mentioned in the previous section, the results from this thesis do not represent all crisis periods. It would therefore be interesting to analyse the impact that the MBV had during different crisis periods and see if the market's perception of bank equity valuation has altered over time. Additionally, even though the MBV is argued to be a driver of tail risk for both US and European banks, the significances vary. We have attributed this difference to regional and cross-country differences in financial reporting and regulation. Thus, another extension to this thesis is to explore the regional differences within Europe. One can analyse how macro- and financial market factors

impact the MBV of banks across countries. The macro factors could include GDP figures, inflation statistics and housing prices, whilst the financial market factors could measure bank concentration and regulatory differences. Additionally, as it is seen that ROA carries more information about tail risk in US banks in comparison to European, one could explore if the macro- and financial market factors are the drivers for this difference and to what extent.

Regarding the second part of our thesis (Explaining the market-to-book value) we have uncovered a suggested link between MBV and CDS spreads. Further insights to this relationship would be valuable to understand how government guarantees affect the underlying behaviours and expectations of investors across security classes. In this thesis, we have used the CreditGrades methodology to convert option prices into CDS spreads, but there may exist better models to proxy for government guarantees. Future research could attempt to estimate government guarantees through a different model and possibly uncover a more robust relationship between government guarantees and equity valuation. Lastly, this thesis proposes that there is a significant relationship between the MBV of banks and their tail risk, as well as a significant relationship between the MBV and CDS spreads. The interlinkages of these relationships could be further analysed by exploring whether tail risk could be estimated directly by using CDS spreads.

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Appendix

Appendix 1. Number of companies

Country	Companies
Austria	3
Belgium	2
Croatia	5
Cyprus	4
Czechia	1
Denmark	13
Finland	2
France	6
Germany	6
Greece	8
Hungary	1
Iceland	2
Ireland	2
Italy	16
Latvia	1
Liechtenstein	1
Lithuania	3
Malta	1
Netherlands	2
Norway	4
Poland	12
Portugal	4
Romania	2
Slovakia	2
Spain	13
Sweden	3
Switzerland	3
UK	10
EU	132
USA	429

Appendix 2. Main regression – US banks

This table reports the results from the main OLS regression, which analyses the relationship between tail risk and the market-to-book value (MBV), return on assets (ROA), return on equity (ROE) and price-earnings ratio (P/E).

$$Return_i^{crisis} = \beta_0 + \sum \beta_J \times X_i^{pre-crisis}$$

where Return is the "bad bank day" return for the respective bank, representing the tail risk, and X represents the variables of interest. All variables are in natural logarithm.

	(A2:1)	(A2:2)	(A2:3)	(A2:4)	(A2:5)	(A2:6)	(A2:7)
MBV	-0.0286***		-0.0266***		-0.0260***		-0.0283***
	(-14.05)		(-13.25)		(-8.232)		(-13.63)
ROA		-0.0275***	-0.0142***				
		(-5.608)	(-3.676)				
ROE				-0.0126***	-0.00235		
				(-10.10)	(-1.381)		
P/E						0.00407**	0.00235
						(2.340)	(1.381)
Constant	0.00156	-0.110***	-0.0457***	-0.0483***	-0.00555	-0.0332***	-0.00555
	(0.872)	(-6.925)	(-3.524)	(-16.81)	(-0.914)	(-6.186)	(-0.914)
Observations	429	429	429	429	429	429	429
R^2	0.330	0.083	0.350	0.179	0.333	0.011	0.333
Adjusted R^2	0.328	0.0805	0.347	0.177	0.330	0.00824	0.330
Country FE	NO	NO	NO	NO	NO	NO	NO

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 3. Control variables

The table reports the results from the OLS regression that estimates the relationship between the market-to-book value (MBV) and tail risk for European banks (A3a) and US banks (A3b), with certain control variables. The construction of these variables is provided in Appendix 5.

$$Return_i^{crisis} = \beta_0 + \beta_1 \times MBV_i^{pre-crisis} + \sum \beta_J \times Control_i^{pre-crisis}$$

where Return is the "bad bank day" return for the respective bank, representing the tail risk, and Control represents the control variables used with the MBV. All variables are in natural logarithm.

Appendix 3a. European banks (A3a)

	(A3a:1)	(A3a:2)	(A3a:3)	(A3a:4)	(A3a:5)	(A3a:6)	(A3a:7)	(A3a:8)	(A3a:9)	(A3a:10)
MBV	-0.00419*	-0.0104***	-0.0110***	-0.00809***	-0.00851***	-0.00703***	-0.0120***	-0.00772***	-0.00820**	-0.00875***
	(-1.913)	(-3.817)	(-3.984)	(-3.530)	(-4.386)	(-3.128)	(-2.980)	(-4.128)	(-2.731)	(-4.251)
Size	-0.00251***									
	(-7.420)									
Book Leverage		-0.000199								
		(-0.228)								
Market Leverage			-0.00199*							
			(-1.967)							
Non-Interest Income				0.00360**						
				(2.690)						
Interest Income					0.00426					
					(1.465)					
Intangible Assets						-0.00140***				
						(-2.903)				
Loans							0.00318			
							(0.382)			
Deposits								0.00825***		
								(2.929)		
Dividends									-0.00204	
									(-1.160)	
Beta										-6.682*
										(-1.745)
Constant	0.0173***	0.00145	0.000625	0.0160**	0.0126	-0.0108**	0.000202	0.00383	-0.00783	-0.000754
	(6.131)	(0.551)	(0.274)	(2.632)	(1.275)	(-2.473)	(0.0750)	(1.348)	(-1.179)	(-0.419)
Observations	132	94	94	105	132	124	65	132	95	132
R^2	0.472	0.210	0.245	0.235	0.177	0.249	0.194	0.272	0.186	0.171
Adjusted R^2	0.464	0.193	0.229	0.220	0.165	0.236	0.168	0.260	0.168	0.158
Countries	28	28	28	26	28	28	18	28	25	28
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 3b. US banks (A3b)

	(A3b:1)	(A3b:2)	(A3b:3)	(A3b:4)	(A3b:5)	(A3b:6)	(A3b:7)	(A3b:8)	(A3b:9)	(A3b:10)
MBV	-0.0101***	-0.0282***	-0.0297***	-0.0281***	-0.0285***	-0.0259***	-0.0285***	-0.0282***	-0.0275***	-0.0286***
	(-4.795)	(-14.72)	(-15.17)	(-13.61)	(-14.08)	(-11.68)	(-14.04)	(-15.01)	(-11.35)	(-14.17)
Size	-0.00785***									
	(-12.83)									
Book Leverage		-0.00455***								
		(-5.025)								
Market Leverage			-0.00448***							
			(-4.386)							
Non-Interest Income				-0.000766						
				(-0.678)						
Interest Income					0.00481					
					(0.798)					
Intangible Assets						-0.00180**				
						(-2.584)				
Loans							0.00623*			
							(1.682)			
Deposits								0.0442***		
								(6.569)		
Dividends									-0.00105	
									(-1.331)	
Beta										-42.74
										(-0.884)
Constant	0.0453***	-0.00905***	-0.00231	-0.00255	0.0151	-0.01000**	0.00379	0.0139***	-0.00323	0.00164
	(12.48)	(-3.111)	(-1.129)	(-0.425)	(0.864)	(-2.435)	(1.640)	(6.049)	(-0.825)	(0.928)
Observations	429	426	426	429	429	326	428	428	358	429
R^2	0.623	0.375	0.360	0.331	0.331	0.343	0.334	0.419	0.337	0.331
Adjusted R^2	0.621	0.372	0.357	0.328	0.328	0.339	0.331	0.416	0.334	0.328
Country FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 4. Adjusted selected control variables

This table shows the results from the selected control variables Size, Intangible Assets, Beta and Non-Interest Income. The data sample in A4:1-A4:3 has 124 observations and A4:4-A4:5 has 105 observations. This is done to provide evidence for the statements in Section 7.2.2, regarding the change in R^2 when dropping observations. The results come from the OLS regression that estimates the relationship between the market-to-book value (MBV) and tail risk for European banks.

$$Return_i^{crisis} = \beta_0 + \beta_1 \times MBV_i^{pre-crisis} + \sum \beta_J \times Control_i^{pre-crisis}$$

where Return is the "bad bank day" return for the respective bank, representing the tail risk, and Control represents the control variables used with the MBV. All variables are in natural logarithm. The construction of these variables is provided in Appendix 5.

	(A4:1)	(A4:2)	(A4:3)	(A4:4)	(A4:5)
MBV	-0.00432*	-0.00407*	-0.00434*	-0.00454*	-0.00505**
	(-1.931)	(-1.768)	(-1.945)	(-1.979)	(-2.385)
Size	-0.00256***	-0.00243***	-0.00255***	-0.00241***	-0.00226***
	(-7.815)	(-8.128)	(-7.735)	(-6.250)	(-5.743)
Intangible Assets		-0.000378			
		(-0.906)			
Beta			-4.569*		
			(-1.909)		
Non-Interest Income					0.00289**
					(2.082)
Constant	0.0181***	0.0144***	0.0179***	0.0172***	0.0289***
	(6.182)	(2.949)	(6.096)	(5.347)	(6.018)
Observations	124	124	124	105	105
R^2	0.480	0.485	0.483	0.386	0.442
Adjusted R^2	0.471	0.472	0.470	0.374	0.426
Countries	28	28	28	26	26
Country FE	YES	YES	YES	YES	YES

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 5. Variable descriptions

This table presents the definitions and data description of the variables used in the study. The data presented represents the data for the US, collected from CRSP/Compustat Merged. The European data, collected from Compustat Global, contains different data descriptions, including: teq [seq]; nicon [ni]; initb [tnii]; lcabg + lcuacu [lg]. The respective US code is presented in []. Additionally, when ceqt did not exist, it was replaced with:
ceqt = seq – pstk – intan
ceqt = ceq – intan
ceqt = at – lt – pstk – intan
The stock market used to calculate the beta was the MSCI World Index.

Variable name	Definition	Data description
MBV	Market capitalization over tangible book equity	$\frac{prc \times shrout}{ceqt}$
ROA	Earnings before interest and expense over total assets	$\frac{ebie}{at}$
ROE	Net income over tangible book equity	$\frac{ni}{ceqt}$
P/E	Market capitalization over net income	$\frac{prc \times shrout}{ni}$
Size	Total assets	at
Book Leverage	Total debt over total assets	$\frac{dltt + dlc}{at}$
Market Leverage	Total debt over market capitalization and debt	$\frac{dltt + dlc}{prc \times shrout + dltt + dlc}$
Non-Interest Income	Non-interest income over total assets	$\frac{tnii}{at}$
Interest Income	Interest income over total assets	$\frac{idit}{at}$
Loans	Total loans over total assets	$\frac{lg}{at}$
Deposits	Total deposits over total assets	$\frac{dptc}{at}$
Intangible Assets	Total intangible assets over total assets	$\frac{intan}{at}$
Dividends	Dividends over total assets	$\frac{dvc}{ceqt}$
Beta	Covariance (stock, market) over variance of the market.	$\frac{cov(i,m)}{var(m)}$