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Systemic risk and the market-to-book value of banks' equity

Florian Meier
41338@student.hhs.se

Yuqing Meng
41253@student.hhs.se

Abstract

The goal of this thesis is to investigate whether market participants considered possible government guarantees when valuing banks' equity before the recent financial crisis and to what extent the market value of banks' equity is useful to estimate their exposure to systemic risk. Using a theoretical approach, we first present our argument that anticipated government guarantees in case of a systemic breakdown lead to financing costs of debt being independent from a bank's exposure to systemic risk. Since debtholders classify their debt repayments as almost riskless due to expected government intervention ("government guarantees") in case of a default in a crisis, they require only little compensation for their contribution. In return, banks increase their exposure to systemic risk to earn additional future cash flows, leading to a higher market-to-book value of their equity.

We test this argument by regressing individual banks' average losses on the worst days during the crisis (as a proxy for their systemic risk exposure) on their market-to-book value of equity before the crisis hit. We find a highly significant positive relationship between banks' market value of equity and their exposure to systemic risk. This leads us to the conclusion that first, market participants priced anticipated government guarantees in banks' market value of equity and second, the market-to-book value of a bank is an indicator for its exposure to systemic risk. Several robustness tests support our findings.

Keywords: Banks, Financial Crisis, Government Guarantees, Market-to-book Value, Risk

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Table of Contents

1. Introduction

The collapse of the US investment bank Lehman Brothers in 2008 marked the peak of a global financial crisis that is considered as the worst economic downturn since the Great Depression. What started with distressed subprime mortgages that seemed to mainly affect the American housing market quickly spilled over to the whole financial industry in the US and eventually, in the whole world. What made this crisis considerably severe is that it did not only affect banks and financial institutions, which were directly involved in the business, but led to a global economic downturn, affecting real growth in different industries. The large negative implications of a possible further breakdown of the world economy led to many governments saving banks in their respective countries from bankruptcy (U.S. Department Of The Treasury, 2012).

The financial crisis of 2008 showed in a dramatic way how strong the different financial institutions in the world are interrelated with each other and the rest of the economy. Especially in the US, where most of the banks saved by a bailout operate, a long public discussion evolved around the question: Why do taxpayers have to save exactly these institutions that were responsible for the crisis in the first place? The answer seems straightforward: The collapse of Lehman Brothers has shown that further failure of institutions that are too big and too interconnected with the rest of the financial industry can cause an even worse downturn, not only for the rest of the industry, but for the whole economy. Many institutions have been saved because they were simply "too big to fail".

In this thesis, we would like to investigate whether the financial system had been aware of this phenomenon before the actual bailouts happened. Did market participants consider possible government guarantees when valuing banks' market values and, if yes, does this help us to obtain information about the current exposure of certain institutions to systemic risk?

We explore this question by looking closer at banks' market-to-book values (MBV) in 2006, the year before the global financial crisis. Using a simple theoretical framework, derived by Atkeson et al (2018), we argue that the MBV can be interpreted as a risk factor, given anticipated government guarantees are priced in the market value of equity.

Government bailouts usually come into play when a bank's losses wipe out all its equity, leading to a state where the institution is unable to pay back its obligations to debtholders. In this case, governments can support them with taxpayers' money to promise for banks' liquidity.

Such bailouts usually happen if a bank's failure to meet its obligations is expected to cause severe additional problems, which is the case in a financial crisis when several institutions at the same time encounter losses. Such guarantees are usually not announced explicitly, but they might be expected by the financial markets and, hence, implicitly priced in banks' market values of equity. An important measure when talking about government bailouts is, hence, banks' potential losses during severe economic breakdowns, called their "tail risk". If the financial system expects this tail risk to be compensated by taxpayers in case of a crisis, cost of debt becomes independent from such risks. Because high risks come with high returns, banks can make additional profits through loading on tail risk without having to pay additional cost for their leverage since debtholders see their contribution as riskless. This leads to rising cash flows, which are priced in the market value of equity of banks.

We test this theory in an empirical study by regressing tail risk (proxied through the average returns of banks on the worst days of the financial crisis) on the market-to-book value of banks in 2006, the year prior to the crisis. This approach is closely related to the work of Meiselman et al (2018). The results show a highly significant correlation between banks' MBV before the crisis and their losses during the crisis. Market-to-book values of equity can explain almost 30% of the variation of banks' tail risk. This leads us to two main conclusions: First, the results indicate that anticipated government guarantees were priced in the market values of banks' equity in 2006. Second, the size of MBV of a bank contains information about its tail risk and might serve as an estimate for a measure of risk in different times. The latter one, however, requires a more cautious formulation: Even though we find MBV to be a significant factor in explaining our measure for tail risk, this does not necessarily mean that MBV is the most important or only important variable in explaining the risk measure. Using several control variables, such as size or leverage, we can show that the explanatory power of MBV to describe tail risk does not stem from its correlation with other values. However, we can also confirm a highly significant correlation of factors other than MBV with banks' exposure to systemic risk.

By applying these findings, we develop a multivariate model to estimate a current tail risk measure in an out-of-sample application. We show that, by looking at MBV and other variables from banks' financial reports, we can explain more than 60% of the variation of our measure for banks' tail risk during the financial crisis. Using the same model to estimate tail risks in 2016, we find that little has changed regarding the total level of expected losses in case of another systemic breakdown compared to 2006. What is interesting is that at the same time, average MBV of banks decreased. This shows that even though market-to-book value seems to be a good indicator for tail risk, other factors must be considered as well when estimating banks' exposure to systemic breakdown.

The remainder of this thesis is structured as follows: Section 2 introduces the background of our research topic and presents the relevant literature in this area. In section 3, we present a theoretical model further describing the connection between government guarantees, tail risk and MBV. Section 4 gives a detailed overview of the design of our empirical analysis and the data we use. Section 5 provides the results and section 6 concludes.

2. Literature review

The main goal of this thesis is to investigate the relationship between a bank's market-to-book value and its risk-taking behavior. To present our reasoning, in this section we introduce banks' characteristics and the potential threat to the economy in a crisis, which lead us to focus on a special kind of risk, systemic risk. In the second step we mention common methods on observing as well as measuring systemic risk. Finally, we give a short overview over other factors influencing a bank's risk exposure.

2.1 Systemic risk and tail risk in the financial system

The start of the global financial crisis through the bankruptcy of Lehman Brothers, described shortly in the introduction, showed how detrimental a failure of a single bank can be for the whole global economy. Furthermore, such a single "systemic event", can lead to the breakdown of other banks. We call this risk where several financial institutions or markets at the same time encounter failure "systemic risk". Systemic risk imposes two main problems for the economy: First, it is costly for economies since a breakdown of the financial sector can lead to a liquidity shortage due to an undercapitalization and hence a hampering of economic growth in general. Negative spillover effects, such as negative performance on bank-dependent firms after a systemic crisis, are noted in literature (Chava & Purnanandam, 2011). Second, potential bailouts of systemically important banks lead to increased cost for taxpayers.

Due to their important role of providing financing to the economy, their high levels of leverage, and their interconnectedness, banks can be especially vulnerable to systemic risk (De Bandt & Hartmann, 2000). This means that they might encounter strong decreases in return or liquidity when other parts of the financial system or market fail.

The high amount of leverage in banks is one reason why financial firms are especially vulnerable in times of a severe systemic crisis, although a high amount of leverage is common in the financial sector and does not automatically imply higher financial stress (DeAngelo & Stulz, 2013). By being financial intermediaries, banks lend out money from creditors to different debtors and perform a maturity transformation, hence turning short term deposits into long term credits. In order to guarantee liquidity, banks must diversify the risk from their debtors by lending out to uncorrelated industrial and private sector participants, which leads them to have lower risk of operational leverage or less industry-specific or idiosyncratic risk. However, financial intermediaries have little methods to differentiate their line of services, and in a competitive setting, they cannot choose the spreads freely, which determine their return rates (Saunders & Walter, 1994). In order to remain profitable to their equity shareholders, banks have to increase their return on equity, a task mainly done by taking on high leverage, which can be paid off in normal times since operational risk is low.

Another idiosyncrasy with banks' business model is that due to maturity transformation banks are reliant on debtors' trust. A single trivial event, i.e. "fake news", could lead to a drop in creditworthiness of an institution and to accumulated deposit withdrawals which could ultimately result in illiquidity of a bank. In other words, banks are not only dependent on their operational business decisions by choosing the right projects and creditors, but also on the beliefs of their debtors regarding general safety and the possibility of bank runs (De Bandt & Hartmann, 2000).

Furthermore, the interconnection between financial institutions through the interbank money market and payment security settling systems, not at last increased through various financial innovations for securitization and other credit risk transfer, leads to a system of contagion. In a systemic crisis, the failure of one bank to meet its obligations can have a tremendous effect on the liquidity of its creditor banks, which could amplify in a "domino" effect. Hence, even though in normal times, banks are relatively safe since their operational risk is very low, they can suffer huge losses during crisis times when several banks experience losses at the same time (De Bandt & Hartmann, 2000).

The high importance of this systemic risk for the financial industry calls for a bank-specific risk measure that focuses on the exposure of an individual bank to a severe systemic crisis. We call this risk "tail risk". Tail risk, hence, reflects the potential loss of a bank in extremely bad times, which is uncertain in normal times. Systemic risk and tail risk are, therefore, closely related. While systemic risk describes the risks for the whole financial system coming from a systemic breakdown, tail risk describes the effects of such an event on one certain bank. The measure is different from traditional risk measures such as the co-movement of returns with the market return, which do not mainly focus on crisis times. The most popular measure, the CAPM-beta (measuring the so called "systematic risk"), for example does not focus on systemic risk since it is mainly focused on the co-movement of banks with the market in normal times rather than on rare systemic downturns. An example is its inability to capture the higher risk during the burst of the housing bubble (Caporale, 2012; Adrian et al, 2015).

The distinct characteristics of banks' risk exposure is the reason for many researchers omitting this sector when making general regressions for risk and return. For example, Fama and French (1992) exclude the financial sector before building their portfolios, and the Fama-French-5-factor model does not seem to explain average returns in the financial sector (Adrian et al, 2015).

Hence, we have to focus on other ways to measure bank risk, which focus on tail risk. In the next section, we describe ways to describe and measure banks' tail risk.

2.2 Measurement of tail risk

We have shown in the last section that banks have relatively low operational risk and, hence, relatively low risk in normal times. Therefore, we focus on the losses of banks in extremely bad times, on their tail risk. Since this risk is not observable, different measures for risk estimation and prediction are mentioned in literature. We will present several ways to estimate such tail risk per bank and explain why the MBV could be a potential explaining factor for tail risk. Before doing so, however, we have to find a way to measure actual tail risk in order to be able to test the explanatory power of different variables. Because tail risk focuses on economic downturns, we can only measure it with sufficient accuracy ex post, after the financial system has experienced a severe crisis.

2.2.1 Ex post measures

The goal of this thesis is to investigate whether MBV can be used to better understand government guarantees and tail risk of banks. In order to do so, we first need a way to measure this tail risk based on real market events. Acharya et al (2016b) construct a simple metric related to systemic risk, which describes the losses of firm on the days with the worst performance of the whole market, the marginal expected shortfall (MES). Furthermore, they argue that this measure is closely related to each firm's contribution to a systemic crisis, the systemic expected shortfall (SES). MES per bank is theoretically defined as follows:

$$\frac{\partial ES_\alpha}{\partial y_i} = -E[r_i | \, R \leq VaR_\alpha] \equiv \; MES_i$$

The sensitivity of the expected shortfall of the overall firm, consisting of different risk factors y, to a specific risk factor y_i, is the marginal expected shortfall of this factor.

In other words, the measure tells us how much an individual bank loses, given the aggregate market return falls below a certain level, here called value-at-risk (VaR) (see also section

2.2.2). The researchers provide an easy but very effective approach of measuring MES: MES is the return of a single bank on the 5% worst days of the market over a certain period, i.e. the return of an individual bank during extremely hard (crisis) times. Hence, MES is an easy way to measure the tail risk of a bank, which we have defined as the performance of an individual institution during extremely bad systemic downturns.

The measure, however, can only be calculated after a crisis has occurred. It can, hence, be used to look back in time and to say something about a bank's tail risk just before a certain crisis, using the observations of this bank during the crisis. It is, however, not an estimate of current, actual tail risk.

2.2.2 Ex ante measures

MES as a measure for tail risk is a simple way to say something about the past. The challenge, however, is to estimate tail risk ex ante, hence, before a crisis occurs. This field of research can be divided roughly in three categories: First, there is a lot of literature focusing on the interdependencies of the whole financial system and how the current state of the system can be measured. These measures, however, do not mainly focus on individual banks. Second, model-based estimation techniques can be applied to look at possible reactions of a bank's portfolio to a systemic crisis. And third, certain variables based on banks' book or market values can be identified, which might be used as proxies for tail risk due to their correlation with the mentioned tail risk measures. We will shortly describe all three categories.

One focus of research is to describe the interdependences of individual banks with the whole system during a crisis in general. Such theories are focused on the sources of a crisis and the interconnectedness of the banking sector, which can lead to an amplified exposure and "domino-effects". One example is the ΔCoVaR by Adrian and Brunnermeier (2016), which integrates spillover effects, by measuring the contribution of an institution i, such as an individual bank, to the conditional VaR of another institution j, such as the whole financial system, given a systemic event. Another approach is by Weiß et al (2014), who apply the measure of lower tail dependence (LTD) which is the probability of the stock returns of an individual bank and the market being in the lower tail. Moreover, Patro et al (2013) identify that stock return correlations among the 22 largest bank holding companies increase with significant market events, and hence can explain systemic risk. They further decompose risk into systematic and idiosyncratic risk and find that recent increases in systemic risk can be attributed towards an increase in correlation of banks' idiosyncratic risk, which confirms the thesis that higher bank interdependence leads to higher systemic risk.

However, models describing mechanisms in the whole system are not useful to describe risk exposures of individual banks. Looking at single institutions, we want to find a way to answer the question: "How would a certain bank react tomorrow if a crisis occurred and the whole financial system would break down, given markets are in a normal state today?" This question is especially important for regulators and supervisory-institutions who try to assess the riskiness of banks for the whole financial system. Such institutions usually use model-based approaches to estimate tail risk. By the Basel Capital Accord II (Basel Committee on Banking Supervision, 2003), as an internal model, banks should use the risk measure of value-at-risk. Value-at-risk (VaR) measures the minimal loss on an asset over a period given a confidence level, hence the probability of the return being smaller than the VaR should be α, such that:

$$Pr(R < -VaR_{\alpha}) = \alpha$$

VaR is a model-based measure that tries to estimate risk directly through assuming certain return distributions. Since the input variables for calculating the VaR are usually dependent on the current market value and its standard deviation, it measures the losses resulting from normal market movements (Allen & Saunders, 2004). This focus on "normal times" has been criticized and led to undercapitalized book exposures in times of the crisis (Basel Committee on Banking Supervision, 2014).

This led to a change in measurement in the Basel framework, replacing it by expected shortfall as the regulators' measurement of tail risk. The expected shortfall measures the expected loss under the condition of a higher loss than the VaR and hence the capital charge from this measure focuses more on risks resulting from really bad events for an individual institution.

$$\mathrm{ES}_{\alpha} = -\mathrm{E}[\mathrm{R} | \mathrm{R} \leq -\mathrm{VaR}_{\alpha}]$$

However, even though this measure focuses on extremely bad events, it still does not capture explicitly what happens to a single bank if all other banks experience bad times, too (Allen and Saunders, 2004). Like value at risk, the measure does not take into account the current state of the market and, hence, does not tell us anything about crisis times.

Besides their focus on normal times, model-based approaches are also criticized because they are easy to manipulate by regulated entities (Behn et al 2016). Since regulators define capital requirements, such as leverage or liquidity ratios, using these model-based approaches, banks that face binding requirements might have a higher incentive to underreport risk (Begley et al 2017).

A third way of measuring tail risk is, hence, to find ratios, which tend to be correlated with tail risk. Such approaches do not try to model tail risk directly, but to proxy it through other measures that are less prone to manipulation.

One work in this field that is very closely related to this thesis is from Meiselman et al (2018), who argue that book returns of banks are a better proxy for tail risk than model-based measures, such as ones using risk weighted assets. They describe a financial institution as an asset portfolio, which should generate higher returns due to higher exposure to systemic risk. Through several regressions, the researchers can show that banks return on equity before the recent financial crisis can explain about 20% of the variation in their tail risk (measured through MES), which is higher than the risk proxy generated using risk weighted assets.

This thesis takes the idea of Meiselman et al (2018) and develops the reasoning further. We use the same idea of using non risk-specific measures in normal times to proxy for tail risk. Using linear regression, we investigate whether MBV of banks before the recent financial crisis would have been a good indicator for their tail risk. MBV is different to other measures that have been proposed in the way that it includes market values, while return or book leverage focus on book values. Hence, the measure includes investors' market expectations about future cash flows, whereas accounting ratios focus on historical data, such as the profitability from the previous year.

By choosing MBV as our explanatory variable we incorporate investors' beliefs in the measure, which allows us to connect tail risk to anticipated government guarantees. If anticipated government guarantees were priced by market participants, they should be reflected in a higher market value of equity of banks.

2.3 Measurement of government guarantees

Recent literature describes the effect of government guarantees on banks' behavior. Due to moral hazard between banks and government, government guarantees might distort banks' decision to take on risk (Calomiris, 1990). Since governments guarantee the payback of deposits in crisis times, these deposits are valued as safer than they would be without guarantees. As a result, banks face lower financing costs, leading them to take on higher risk (see section 3). Gropp et al (2013) show in a natural experiment, that banks removed credit risk after explicit government guarantees were removed, a behavior not observed in the control group. Allen et al (2018), however, show that government guarantees do not only have negative distortionary effects: Deposit insurance might still be welfare improving, since it provides banks with liquidity, which lead banks to be more efficient in liquidity transformation. Further literature measures government guarantees by comparing differences in bond credit spreads of different institutions, whereas systemically important institutions are proxied by looking at their size. Acharya et al (2016a) find that the largest financial institutions are less sensitive to changes in bond credit spreads, compared to smaller financial institutions. Since this difference in sensitivity does not hold for non-financial firms, the authors conclude that this relationship can be attributed to government guarantees, which allow large financial firms to borrow at subsidized rates. Similarly, Gandhi & Lustig (2015) find out that a portfolio with a long position in a stock portfolio of the largest U.S. commercial banks and a short position in a stock portfolio of the smallest banks underperforms an equally risky portfolio of all non-bank stocks. This arbitrage opportunity implies that large banks do not have to pay as high required returns as large firms in general. The difference can be explained by the government guarantees, which apply for large institutions rather than for small ones, due to their importance for the financial system. Kelly et al (2011) compare the price of out-of-the-money index options with the price of a basket of out-of-the-money options of the individual banks. They argue that index options are more exposed to systematic risk, while the basket is more exposed to individual risk. Since systemic risk is guaranteed by the taxpayer, index options should trade at a higher price compared to the basket of individual options. They find evidence that this is the case, supporting the argument that anticipated government guarantees in case of a systemic crisis are priced in the option premium.

In the next section, we will further describe the connection between anticipated government guarantees, MBV and eventually, tail risk.

3. Theoretical model

In this section, we use a simplified version of the two-state model by Atkeson et al (2018) to illustrate that the market-to-book value can be indeed a risk factor for banks. In the model, under the assumption of government guarantees banks have an incentive to choose the risky project over the risk-free project, which leads them to loading on more risk in expectation for government bailout in a possible crisis. Additionally, we show that an increase in the risk of the project leads to a higher market-to-book value.

The model we present assumes that government guarantees influence the behavior of the whole financial industry. It explains why the participants act differently under the assumption that they are not accountable for the possible negative consequences of their behavior, leading to negative social externalities. In our model, however, not only banks face moral hazard, the whole financial system expects these implicit guarantees. Debtholders offer banks lower interest rates since they expect their debt to be bailed out in a crisis, thus inducing banks to choose risky projects. Equityholders also benefit from these government guarantees since future earnings increase, pushing the market price of equity, due to lower financing costs. Since the consequences of a breakdown do not have to be carried by any party of the financial firm, in this model, but from the taxpayers due to its spillovers to the whole economy, this creates negative social externalities for the society.

It is important to mention that here, we talk about the whole financial industry, rather than one individual bank. This representative agent model models the behavior of one bank and one financier, in order to describe how banks and debtholders would work in a financial system.

3.1 Impact of government guarantees on the financial system's risk-taking behavior

In our model, the financial industry consists of two participants. The bank (B) starts with a certain amount of its own money (N). Furthermore, it gets further resources from the debt-holder, here called financier (F), who requires the risk-free compensation R^f for its contribution. As a debtholder, the financier has a senior claim to the equityholder, which means that the interest is paid back first. The bank invests all the money (I), financed by leverage ρ, such that $I \times \rho$ equals the dollar-contribution of the financier and $I \times (1 - \rho)$ equals the bank's own fraction, N.

Now, we assume a two-state-model. In the first state, the bank can decide between two possible projects to invest in, a risky project and a safe project. These two projects will have different outcomes in the second state, depending on which second state will occur, the crisis state or the normal state:

	safe project	***risky project***
normal state n	$\mathrm{R^f}$	$\mathrm{R^n > R^f}$
crisis state c	$\mathrm{R^f}$	$\mathrm{R^c < R^f}$

With R^f being the risk-free rate and q_c being the risk-neutral probability of the crisis state, c. Furthermore, we assume perfect competition and risk-neutral probability:

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

We now focus on the financier, who requires an expected compensation of R^f for its investment, regardless of the outcome of the economy. If the bank choses to invest in the safe project, the financier gets a guaranteed dollar payoff of $I \times \rho \times R^f$. If the bank invests in the risky project and the normal state occurs, the financier will get $I \times \rho \times R^f$ too, since $R^n > R^f$, by definition. However, if the bank decides to invest in the risky project and the crisis state occurs, there are two options:

1. $I \times R^c > I \times \rho \times R^f$: In this case, there is no risk for the financier. Regardless of which project is chosen, it will get a safe payoff of $I \times \rho \times R^f$, even in the crisis state.
2. $I \times R^c < I \times \rho \times R^f$: Given the risky project is chosen, the bank is unable to pay off its obligation of $I \times \rho \times R^f$ to the financier in the crisis state and, hence, choses bankruptcy. In this case, the financier gets what is left, $I \times R^c$, which is smaller than its required compensation.

The question now is: Which project is chosen under which circumstances, given the credible condition that $R^c < \rho \times R^f$? This depends on whether there are government guarantees.

3.1.1 Decision without government guarantees

To agree to the risky project, the financier requires a higher return than R^f in the normal state to make sure the expected payoff still equals R^f. Or mathematically, the financier wants to make sure that:

$$(2)\ [(1 - q_c) \times R^F + q_c \times R^c] \times I = \ I \times \rho \times R^f$$

or

$$(3)\ R^F = \frac{\rho \times R^f - q_c \times R^c}{(1-q_c)}$$

where R^F is the financier's payoff in the normal state. In other words, even though the financier only requires the risk-free rate, the bank has to promise more due to crisis risk. This leads to bank's expected dollar return of the risky project:

$$(4)\ (1-q_c) \times (R^n - R^F) \times I$$

(Due to the derivation above, R^F is the fraction of the whole investment I that goes to the financier. The leverage ratio ρ is already included)

We use the fact that $R^F = \frac{\rho \times R^f - q_c \times R^c}{(1-q_c)}$ and we rearrange (4) as follows:

$$(5)\ (1-q_c) \times \left(R^n - \frac{\rho \times R^f - q_c \times R^c}{(1-q_c)}\right) \times I = \left((1-q_c) \times R^n - \rho \times R^f + q_c \times R^c\right) \times I$$

Knowing that, by the definition of risk neutral probability (1), we can write the banks' expected return for the risky project as:

$$(6)\ (1-\rho) \times I \times R^f \text{ or } N \times R^f$$

It can be easily seen that this exactly equals the banks' expected return of the safe project. Hence, for the case that $I \times R^c < I \times \rho \times R^f$, it is never profitable to choose the risky project, assuming no government guarantees. In our model with only one representative agent, no risky projects would be executed.

Our model assumes that the financier can control the decision of the bank to choose the riskless project. Often, however, the financier has to make the decision for financing before the bank decides to invest in the risky or riskless project, i.e. a state of moral hazard, since the actual action is unobserved. In a non-repeated game, thus facing no consequences for its actions in the previous period, the bank might have an incentive to deviate, since it could earn more if it chose the risky project while paying the riskless rate for financing (see 3.1.2). The financier would expect this action and demand only R^F. Since this is a state where no one could change their action to get to a state where they are better off, this is a Nash equilibrium, in similar manner to the prisoner's dilemma. In practice, financiers have the options to exert control using covenants and banks also have to care about the financiers to obtain future financing, which makes this option less likely.

3.1.2 Decision with government guarantees

Now, we assume that there is a government, ready to guarantee that the financier will always get a return of R^f on its money, or $I \times \rho \times R^f$ in dollars, respectively. For the safe project, nothing changes in this case. Both, financier and bank get a guaranteed payoff of R^f on their contribution. Assuming that the risky project is chosen and that the normal state occurs, nothing changes either. However, in case of a crisis, the government now guarantees a payoff of $I \times \rho \times R^f$ for the financier, meaning that it closes the gap by paying out $I \times \rho \times R^f - I \times R^c$. This means that the financier does not require R^F from above anymore since its payoff will be $I \times \rho \times R^f$, even in the crisis state. The expected return for the bank, hence, becomes:

$$(7)\ (1 - q_c) \times (R^n - \rho \times R^f) \times I$$

We also rearrange this equation:

$$risky\ payoff_{bank,gov.guarantee} = [(1 - q_c) \times R^n - (1 - q_c) \times \rho \times R^f] \times I =$$

$$(8)\ \left[(1 - q_c) \times R^n + q_c \times \boldsymbol{\rho} \times \boldsymbol{R^f} - \rho \times R^f\right] \times I =$$

We know from above that the bank's payoff for the safe project equals its payoff for the risky project without government guarantees, see assumption in (1):

$$(9)\ (1 - \rho) \times I \times R^f = [(1 - q_c) \times R^n + q_c \times \boldsymbol{R^c} - \rho \times R^f] \times I$$

The equations are almost identical and only differ in the bold terms, which enter with a positive sign. Since we know that $\boldsymbol{\rho} \times \boldsymbol{R^f} > \boldsymbol{R^c}$ by assumption, the financial system prefers the risky project, given the government guarantees a riskless payoff to the financier. In our model this means that, even though the government does not guarantee any payoff directly to the bank, it still incentivizes the financial system to take risk through a guaranteed payment to the financier in the crisis state, leading to lower capital costs for the bank if it chooses to take risk. In this setting, moral hazard between the financier and the bank does not exist, since a new Nash equilibrium can be achieved, with the guarantees of the government. However, this imposes a new problem of moral hazard between the financial system and the government, i.e. taxpayers. The government cannot control the actual risk taken by the financial system, even though it will bail out the system in case of a systemic crisis.

3.2 Impact of government guarantees on banks' MBV

We now would like to find out how these findings connect to the banks' market-to-book value of equity. Since the bank contributes N in the first state of our two-state-model, this reflects the book value of equity. We present a way to describe the market value of equity. Again, we start assuming there are no government guarantees.

3.2.1 MBV without government guarantees

We show in (section 3.1.1) that in the absence of government guarantees, the bank would choose the riskless project, if no moral hazard exists. Nevertheless, we show that the market-to-book value would be the same, no matter if both participants could agree on the riskless project or not:

- When choosing the riskless project, the return for the bank would be R^f, and the payable amount to the financier would be $R^F = \rho \times R^f$, leading to a present value of the market value of equity in the first state of:

$$(10)\ M = \frac{1}{R^f} \times [(R^f - \rho \times R^f) \times I - N + M] = N$$

- When choosing the risky project, the return for the bank would be R^n in the normal state and zero in the crisis state, the financier would require a return equal to $R^F = \frac{\rho \times R^f - q_c \times R^c}{(1-q_c)}$. The present value of the market value of equity in the first state of:

$$(11)\ M = \underbrace{\frac{1}{R^f}}_{\text{Discount Factor}} \times \underbrace{(1-q_c)}_{\text{Probability of good state}} \times \Bigg[\underbrace{\underbrace{\left(R^n - \frac{\boldsymbol{\rho \times R^f - q_c \times R^c}}{\boldsymbol{(1-q_c)}}\right) \times I - N}_{\text{Banks' earnings (dollars) – banks' investment (dollars) =banks' profit (dollars)}} + \underbrace{M}_{\text{Market Value of equity before investment}}}_{\text{Market value of equity in the second state, given no crisis occurred (otherwise, this term equals zero)}}\Bigg]$$

Using the fact that $(1-q_c) \times R^n + q_c \times R^c = R^f$ and $\frac{N}{1-\rho} = I$ we can rewrite this term as:

$$(12)\ M = \frac{1}{R^f} \times (1-q_c) \times \left[\frac{1-\rho}{1-q_c} \times R^f \times \frac{N}{1-\rho} - N + M\right] = N$$

Hence, no matter which project the bank chooses (this depends on our assumptions), without government guarantees, $M = N$ and, hence, $MBV = 1$.

3.2.2 MBV with government guarantees

If we extend the model again and include government guarantees, we rewrite the definition of M above, but set $R^F = \rho \times R^f$. We get

$$(13)\ M = \frac{1}{R^f} \times (1 - q_c) \times \left[\left(R^n - \boldsymbol{\rho} \times \boldsymbol{R^f}\right) \times I - N + M\right] > N$$

We know that $\rho \times R^f > \frac{\rho \times R^f - q_c \times R^c}{(1-q_c)}$, the rest of the formula is equal to (11). We can see that in this case, the market value of equity is larger than in (11), hence $M > N$, leading to a MBV larger from one. An illustration of this using a simple example can be found in the appendix (example 1).

Looking at this model, anticipated government guarantees lead to debtholders taking their contribution for granted by the state and, hence, for risk-free, regardless of the bank's exposure to systemic risk. This leads to a higher expected return of risky projects and, hence, to higher cash flows in normal times. These higher future cash flows are priced in the market value of equity, leading to an MBV greater than one. However, this MBV greater than one also reflects higher losses of banks in case of a crisis, given government guarantees are considered in the market value of equity.

3.3 Comparative statics

We have seen that, given the model holds, a MBV higher than one is an indicator for anticipated government guarantees influencing decision making in the financial market. Now, we want to see if we can also infer something about the size of the MBV. Does a relatively high MBV indicate a relatively high tail risk and vice versa?

First, we determine how a change in R^N would influence the MBV, by computing the sensitivity using the partial derivative of equation (13).

We compute the MBV given government guarantees from (13):

$$\frac{M}{N} = \frac{1}{N} * \frac{s}{1-s} * [(R^N - \rho * R^f) * I - N]$$

With $s = \frac{1-q_c}{R^f}$

And derive it with respect to the return in normal times.

$$\frac{\partial M/N}{\partial R^N} = \frac{I}{N} * \left(\frac{s}{1-s}\right)$$

The partial derivative after return in normal times is positive if all two parts are positive:

- $\frac{I}{N}$: This term is the asset-to-equity ratio, which is a form of leverage. The higher the asset-to-equity ratio, the higher the leverage and the higher the effect of a higher tail risk on MBV. Since assets and equity are never negative, this term will always be larger or equal to one.
- $\frac{s}{1-s}$: This term comes from discounting for uncertainty and opportunity cost. Since s will be larger than zero, but smaller than one, the term will be larger than zero as well.

Hence, the MBV reacts positively to an increase in return in the normal state. The multiplier depends on leverage and the probability of the crisis and the discount rate. From (1), we know that an increase in return in the normal state must lead to a decrease in the return in the crisis state. Therefore, we compute how a change in R^c would influence the MBV, by plugging in equation (1):

$$\frac{\partial M/N}{\partial R^c} = -\left[\frac{I}{N} * \left(\frac{s}{1-s}\right) * \frac{q_c}{1-q_c}\right]$$

We see that this term is similar to the derivation above, with a negative sign and a third term:

- $\frac{q_c}{1-q_c}$: This term describes the ratio of the risk-neutral probability of the crisis state and the probability of the normal state, which is positive. The smaller the probability of the crisis state, the smaller the term.

The model thus predicts, that a change in the riskiness of the return in the crisis state will lead to an adverse change in the market-to-book value. Hence, a decrease in the crisis return, or an increase in tail risk, will lead to an increase in the MBV, given anticipated government guarantees are considered. Furthermore, leverage seems to have an impact on correlation between crisis return and MBV as well. The model indicates that a higher level of leverage leads to a stronger correlation of tail risk and MBV.

3.3.1 Limitations

The model described above explains the connection between the variation in tail risk (R_c) and the variation in MBV of banks. In section 5, we will test this connection with an empirical model. We take a closer look at the recent financial crisis and regress the returns of banks during the crisis (“tail risk”) on their MBV in 2006 (“normal times”). Having this empirical study in mind, it is important to elaborate on the limitations of the theoretical model described before.

First, the model applied is a highly simplified model, which only focuses on the presence of anticipated government guarantees affecting tail risk and, hence, the MBV of banks. In reality, there is a number of other factors such as investors’ beliefs or other factors not captured in the book value of equity (see section 3.4.1). However, such other factors are difficult model and might depend on factors attributable to investors’ discretion.

Second, we use a two-stage model to describe continuous events. In the real world, we cannot easily differentiate between the normal and crisis state. In our empirical model we proxy the normal state, thus the state of the economy, which is unaffected by crises, through taking market and accounting data from the pre-crisis year (2006). After, we aggregate the average returns from the three years during the financial crisis to compute our proxy for returns in crisis times. In reality, tail risk (as the *possible* returns in case of a crisis) directly affects MBV without any time lag.

Third, it is very tough to empirically test causality. Our theoretical model shows the mechanism that the differentiation between normal and crisis state returns in the two-stage model leads to an MBV greater than one in the presence of government guarantees. We further show that a decrease in the crisis return leads to an increase in market-to-book value. In our empirical model we regress tail risk on MBV, which allows us to formulate conclusions on correlation, not on causality.

Fourth, since our model is a representative agent model with only one bank and one financier, it only explains a partial view. In our empirical model, we look at over 400 individual banks, which differ in their characteristics regarding asset portfolio, leverage, profitability, etc. However, even with these differences, we use the theoretical model to understand the mechanism behind the regression.

3.4 Hypotheses development

We have seen that the MBV is correlated to a bank’s tail risk in the presence of government guarantees. In this section, we further describe what these findings mean for the economy and we present some literature in this area. Furthermore, we formulate three main hypotheses that we expect to approve in our empirical study in section 5, where we regress banks’ tail risk on several measures including MBV, ROE and PE-ratio.

3.4.1 Market-to-book value

The MBV is defined as the market value of equity divided by the book value of equity of a company or the dollar price investors are willing to pay for every dollar of book equity of a firm. In literature the market-to-book value has been interpreted as a proxy for expected return on equity (Graham et al, 1962), as an indicator of mispricing of stocks (Rosenberg et al 1985) and as a proxy for risk (Fama & French, 1992). Conventional interpretations, such as the classification into value vs. growth stocks (Chan et al 1995), however do not make sense in the banking sector. The MBV for banks can have a different meaning compared to other industries, since banks usually have different types of assets. They only hold a few real assets, and most of the banking assets are often liquid and traded in the market or are very similar to traded assets. Hence, they are reported marked-to-market rather than on amortized costs, which is why banks' MBV should be closer to one. However, it will rise above one, if investors expect certain cash flows, which are not priced in the book value of equity (Bogdanova et al 2018). This is also referred to as franchise value or charter value (Keeley, 1990; Calomiris & Nissim, 2014; Sarin & Summers, 2016; Chousakos & Gorton, 2017). This difference between market and book value of equity, which can stem from beneficial market circumstances (Bogdanova et al 2018) or intangible assets entailing increased future profitability (Calomiris & Nissim, 2014) for example through a potential source of private customer information or through market entry barriers and oligopolistic behavior (Chousakos & Gorton, 2017). Another interpretation of the difference between market and book value of equity, however, can be due to implicit government guarantees (Atkeson et al, 2018), as described above.

To discuss implications of these theories, we first look at historical values. Figure 4 (see appendix) shows the historical development of the MBV of the US banking sector from 1976 to 2016, calculated from the data in our sample (see section 4.2). The value reflects the sum of the market value of equity of all banks divided by the sum of the book value of equity of all banks at year end. We observe a steady increase of the ratio until 1997, followed by a slight drop in MBV. This might be explained by the dotcom bubble. After, MBV rises again until 2006, the year before the global financial crisis, to over 3. The global financial crisis leads to a strong drop in banks' MBV to almost 1, followed by a slight recovery to over 2 in 2016. Since we do not observe a return to pre-crisis market-to-book values of banks in the years after the financial crisis (Sarin & Summers, 2016), this could entail two potential implications. First, it could mean that investor confidence in banks has not been fully restored, leading to lower equity valuation, potentially accelerated through stricter regulations. This would imply that stricter regulatory measures hampered banks recovery leading to “banking illness” (Chousakos & Gorton, 2017) and even increased market leverage (Sarin & Summers, 2016). On the other hand, according to Atkeson et al (2018) a lower post-crisis MBV valuation could simply mean that banks’ pre-crisis MBV contained high valuations of potential government bailouts, which are less prevalent in post-crisis years due to stricter regulations aiming to enforce lower risk-taking.

We follow this argument. The theoretical framework argues that the potential bailout through taxpayers increase the safety of banks’ debt and thus decreases the payable interest rate, which means that risky projects become more profitable for banks. This leads to banks taking more risky projects, which is captured in the market value of equity. Hence, we argue that the difference between market and book value of equity stems from a rational source of pricing externalities, such as implicit government guarantees. Following, the MBV should increase with lower tail return (i.e. higher tail risk), given the presence of anticipated government guarantees. If this assumption is true, we should find a negative relationship between MBV and tail return. This leads us to our first hypothesis.

H1: *There is a negative relationship between the market-to-book value in normal times and returns on bad days.*

If this hypothesis holds, it is a strong sign for the presence of government guarantees. Moreover, our model suggests that the effect should be stronger with higher leverage.

3.4.2 Return on equity and return on assets

Both ROE and ROA are commonly used profitability ratios to compare the financial performance across firms. ROE is defined as the earnings attributable to equityholders, usually net income, scaled over the book value of equity. ROA is defined as the earnings attributable to equity- and debtholders, usually earnings before interest expense (EBIE), scaled over the book value of assets.

In the two-state frictionless model described above, we assume that the investor, after applying risk-neutral probabilities, will expect the same return from the risky project than the risk-free rate. This means that under the assumption of a constant risk-free rate, an increase in the expected return on assets in the normal state will have an adverse effect on the expected return on assets in the crisis state and vice versa. ROE, hence, should increase with tail risk, i.e. decrease with the return on crisis days.

Looking at risk and ROE, we always have to take into account leverage as well. Since investment decisions are made by equityholders and investors, banks are focused on increasing ROE instead of ROA, which might create false incentives. ROE increases with leverage ceteris paribus in a setting with discriminating taxes, which gives incentives to increase leverage (Modigliani & Miller, 1958). This effect is even stronger in the presence of government guarantees, which leads to extremely cheap leverage. Furthermore, low interest rates on debt leads to banks underestimate their own asset risk. This leads to increased leverage ratios and higher risk, reflected in a higher return on equity (Acharya & Franks, 2008).

Meiselman et al (2018) directly investigate the correlation of ROE and tail risk, using the same method that we are using in this paper. They find a significant relationship between the return on equity of American banks in 2006 and their stock market returns on the worst days of the financial crisis (as a proxy for tail risk). They argue that banks can be looked at as asset portfolios with a certain exposure to systemic risk. The higher this exposure, the higher the returns, following the CAPM.

The historical development of the average ROE (see appendix, figure 5) shows a constant varying ROE of around 0.14 from 1976 to 2006, when we observe a strong decrease in banks' ROE during the global financial crisis to almost 0. Again, we observe a slight recovery of ROE after 2010 to around 0.11 in 2016. In line with our argumentation for MBV, this difference between pre- and post-crisis levels of ROE could either indicate a hampering of banks' business models or lower risk taken (Meiselman et al, 2018).

We, hence, also expect a negative relationship between ROE and return on crisis days in our regressions.

3.4.3 Price-earnings ratio

The price-earnings ratio is defined as price per share over earnings per share or market capitalization divided by earnings. As a valuation multiple, it reflects the price investors are willing to pay per unit of earnings. Since the market value of equity can be reformulated as expected future earnings, the PE ratio can be interpreted as the ratio between future vs. current earnings of a firm. A relatively high PE-ratio, hence, means that investors are willing to pay more for a certain company compared to another company with the same current earnings in expectation of stronger earnings growth. Interpretation of the PE-ratio range from being an earnings growth indicator (Cragg & Malkiel, 1982) to a risk factor (Ball, 1978). From looking at the historical development, the average PE has steadily increased in our time frame from

1976 to 2016 (see appendix, figure 6). Interestingly, the main trend, after accounting for drops of the ratio after the dotcom bubble or the global financial crisis, is still increasing, not showing an indication of mean reversal.

Existing literature about the price-earnings ratio presents contradictory findings. On the one hand, high PE ratios are found to be followed by high returns, leading to mean reversion of the ratios in the long-term (Campbell & Shiller, 1998), indicating that market expectations are correct on average. On the other hand, persistently increasing PE, have often initiated crises and bubble (Collyns & Senhadji, 2002), which are a source of irrational market expectations. Hence, the effect of PE is two-edged: If investors were rationally expecting a crisis, low PE ratios should precede firms with a high tail risk, however if investors had irrational beliefs, a high PE ratio should be an indicator of a high tail risk.

3.4.4 Decomposition of MBV into ROE and PE-ratio

We have seen that MBV and ROE should, in theory, have a negative correlation with banks' returns in crisis times. Furthermore, it is not clear how PE-ratios and tail risk are connected to each other.

Since market-to-book value can be decomposed into return on equity and price-earnings ratio, and return on equity is not found to indicate the price-earnings ratio (Penman,1996), we explore whether the effect of the MBV on tail risk can be broken down into an effect from ROE and an effect from PE.

$$MBV = ROE \times PE$$

This shows us that all the information contained in ROE and PE is also included in the MBV. The MBV, hence, should always explain at least as much as ROE and PE together. This leads us to our second hypothesis:

H2a: *Return on equity does not explain any variation in tail risk that cannot be explained with the market-to-book value.*

H2b: *Price-earnings-ratio does not explain any variation in tail risk that cannot be explained with the market-to-book value.*

By taking logarithms, we can decompose the equation into an addition:

$$\ln(MBV) = \ln(ROE) + \ln(PE)$$

Hence, we propose a logarithmic relation between ROE, PE and MBV. This should lead to the following regression:

$$\mathbf{ln}(\boldsymbol{return_{crisis}}) = \beta \times \ln(\mathrm{MBV}) \equiv \beta \times \ln(ROE \times PE) \equiv \boldsymbol{\beta} \times \mathbf{ln}(\boldsymbol{ROE}) + \boldsymbol{\beta} \times \mathbf{ln}(\boldsymbol{PE})$$

This means that, by regressing the logarithm of tail risk on the logarithm of PE and ROE, we should get the same coefficients for PE and ROE. If this is the case, we can conclude that ROE and PE together do not contain any information that is not already contained in the market-to-book value, which is our third hypothesis:

H3: *Return on equity and price-earnings ratio together do not contain any information that is not contained in the market-to-book value.*

In the next section, we will describe our methodology to investigate the hypotheses developed above in detail, before we provide our findings in section 5.

4. Research design and methodology

The goal of this thesis is to find out more about the relationship between banks' tail risk and their market-to-book value. In the last section, we have described the theories behind this issue. Now, we would like to test our findings through several regressions. The main regression of interest will be:

$$return_i^{crisis} = \beta \times MBV_i^{pre-crisis}$$

In this section, we further describe how we design our empirical study and which data we use.

4.1 Research design

Using empirical data from 470 US banks in the time shortly before and during the recent financial crisis, we would like to test if our empirical results confirm the mechanisms from the theoretical model. We investigate whether there should be a positive relation between the MBV of a bank and its tail risk (i.e. a negative relation between MBV and crisis return), since this gives us a hint about whether government guarantees priced in the MBV serve as a risk factor, because they incentivize the financial system to take risk. Then, we should find evidence that possible future cash flows from governments payouts were reflected in banks' market values of equity in 2006, the year prior to the financial crisis. It is important to mention that we look at the tail risk of the individual banks, since it is a proxy for their exposure to systemic risk.

We will investigate whether we find such a connection using the methodology developed by Acharya et al (2016b) and used by Meiselman et al (2018). As described in section 2, it is not possible to directly observe tail risk. We will, hence, proxy this risk for our regression through the marginal expected shortfall (MES) (see section 2). Since we can only measure the MES ex post, we have to work with past data. To test whether MBV in normal times is a good measure for tail risk, we regress the MBV of banks in 2006, the year before the recent financial crisis, on their MES during the crisis. MES during the crisis is, hence, a proxy for tail risks banks were exposed to in 2006, just before the crisis, i.e. in normal times.

In line with Meiselman et al (2018), in order to calculate MES, we use stock market returns since holding period returns act quickly on recent events.

4.2 Data and methodology

The sample is constructed in a similar manner to Meiselman et al (2018). We examine daily stock market returns, annual income and balance sheet statements for financial firms in the U.S. Our source for daily stock market data is from the database of the Center of Research in Security Prices (CRSP), accessed through Wharton Research Data Services (WRDS), and we access the merged CRSP/Compustat database for data on annual income and balance sheet data.

Daily stock market data is taken in the time period of 1 July 1926 - 31 December 2016 in the stock markets NYSE, AMEX, NASDAQ & ARCA. We limit our stock data to firms with available data and with actively traded, ordinary common shares.

Accounting data is taken in the time period of January 1976 - December 2016 per fiscal year. Financial firms are defined as banks included in the CRSP/Compustat joined database bank annual, which includes banks with the following Standard Industrial Classification (SIC) codes: 6020, 6021, 6022, 6029, 6035 and 6036. This includes different types of commercial banks and savings institutions.

We aggregate daily stock market data and accounting data on the basis of PERMCO and create an unbalanced panel of 470 observations. We use the following ratios for our main regression, detailed definitions can be found in appendix, table 17:

$$ROE = \frac{Net\ income}{Tangible\ book\ equity} \qquad ROA = \frac{EBIE}{Book\ Assets}$$

$$MBV = \frac{Market\ value\ of\ equity}{Tangible\ book\ equity} \qquad PE\ ratio = \frac{Market\ value\ of\ equity}{Net\ income}$$

For profitability measures, we use the return on assets and return on equity. We construct our return on assets correspondingly to Meiselman et al (2018) by dividing the earnings before interest expenses (EBIE) by book assets. We use EBIE as a gross profit measure to proxy earnings to equity- and debtholders, calculated by adding back interest expenses and taxes to net income. Alternatively, we add interest expense back to pre-tax income, in case the data is not available.

For the return on equity, we calculate the return on tangible equity, by dividing net income by tangible equity. We choose the measure of tangible equity since recognition of intangible assets in the balance sheet is loosely defined and thus can be subject to the discretion of company accounting (IAS 38). Also, in a case of liquidation intangible assets might not be liquid enough to sell it for the recognized value, which differentiates it from tangible assets. Hence, we exclude intangible assets to have a clean measure, which is less subject to creative accounting, in line with Meiselman et al (2018).

We construct the market-to-book value as market value of equity, obtained through the daily stock data, divided by tangible book equity. We define the price-earnings ratio as the market value of equity over net income. Since we take both measures from the end of the year, this equals the common measure of share price over earnings per share (for details, see appendix, table 17).

Following Meiselman et al (2018) and Acharya et al (2016b) we construct a measure for banks' tail risk by taking average holding period returns during the worst days in the financial crisis. This is done in the following way: First, we define the worst 5% days from 1 July 1926 - 31 December 2014. After, we take the average holding period returns of banks on the subset of the 5% worst days that occurred in the financial crisis.

We define "5% worst days", by constructing a measure for the worst days in the financial sector using the 5% lowest value weighted returns from the Fama and French 48 Industry Portfolio (industry 44 of 48), thus "bad bank days". Meiselman et al (2018) compares these results with the alternative measure of "bad market days" as the worst days of the market, by identifying the 5% worst value weighted returns of the entire market portfolio. Even though both measures have different interpretations, we find similar results for the main regression. In the following parts, we will only use "bad bank days" to approach the worst days for computing tail risk.

Following, we compute the simple annual average of daily stock market returns of these worst days during the financial crisis for each company on the basis of the permanent company identifier (PERMCO), which is our measure of systemic risk, denoted as tail risk, per bank.

We standardize all our variables to have a mean of zero and a standard deviation of one and run several regressions in the following style:

$$return_i^{crisis} = \beta_0 + \sum \beta_j * variable_i^{pre-crisis}$$

5. Findings

We explore the relationship between our market and accounting values on the tail risk through several regressions. In table 2, we compare the regression using MBV to the regression using return on equity, return on assets and price-earnings ratio. We show that MBV is a better explanatory variable in our regression on tail risk than ROA, ROE and PE by looking at significance, the coefficient and the partial R^2. In our second step, we expand on the question whether ROE and PE individually have a higher explanatory power than the MBV, applying a logarithmic decomposition (table 3). By applying the logarithmic decomposition and finding the estimates for the logarithmic values we find that ROE and PE together do not significantly explain more than only looking at MBV. Finally, we explore the relationship between the market-to-book value and other ratios, revealing about an individual bank's characteristics. In an application, we try to predict the tail risk in 2016 with a model using different variables and compare this to the tail risk estimated for and in 2006. Using two models, we do not find a significant difference in 2006 and 2016 levels of tail risk.

5.1 Main regressions

For our main regressions, we obtain the following summary statistics in table 1. The return on assets varies from 2.02% to 7.93%, with a mean of 4.1%. The ROE varies from 1.13% to 78.68%, with a mean of 13.7%. The MBV value varies from 0.81 to 8.84 with a mean of 2.39 and the price-earnings ratio varies from 4.84 to 129.5 with a mean of 21.68.

Table 1: In this table, we show the summary statistics of key variables used for the regressions. "Bad bank days" are the 5% worst performing days of the Fama French banking industry portfolio from Jul 1926 to Dec 2014 with the lowest-value weighted return. "Bad market days" are the 5% worst performing days of the value weighted market index return from Jan 1926 to Dec 2014 with the lowest-value weighted return. Average bad-day returns are calculated from bad days between 1 Sep 2007 and 1 Oct 2010. The construction of the variables is explained in table 17.

Summary statistics for main regression

Statistic	N	Mean	St. Dev.	Min	Max
Return on bad bank days (%)	470	-2.10	1.68	-6.98	1.52
Return on bad market days (%)	469	-2.50	1.95	-7.91	3.31
Equity (billions)	470	0.78	4.07	0.01	55.75
Assets (billions)	470	16.07	102.45	0.10	1,459.74
Return on Assets (%)	470	4.10	0.77	2.02	7.93
Return on Equity (%)	470	13.70	7.96	1.13	78.68
Market-to-book value	470	2.39	0.97	0.81	8.84
Price-earnings ratio	470	21.68	14.81	4.84	129.50

Table 2 shows the regression results for the estimation of tail risk using MBV. In this table we proxy tail risk by looking at the average return on the "bad bank days". By looking at "bad market days", we obtain similar findings (see appendix table 12). In table 2, we see a negative significant correlation between the MBV and return on bad days (1). An increase in the MBV of one standard deviation leads to a decrease of 0.540 standard deviations in the return on bad bank days. We compare these to the variables of the original Meiselman et al (2018) paper, ROA (2) and ROE (5) in terms of estimate, significance and coefficient of determination. Due to standardization we can compare the estimates of the different regressions. We see that the estimate of the MBV (-0.540) is stronger negative than the estimates of both ROA (-0.280) and ROE (-0.441) and, hence, is a larger factor in explaining tail risk variations. We observe a higher t-value, hence a higher significance, of MBV (-13.88) than both ROA (-6.31) and ROE (-10.62). However, all three variables are significant at the 0.1%-level in the simple regression. PE shows a positive significant estimate (0.095), in contrast to the other three variables, with a lower significance level (5%). Hence, an increase in PE leads to a decrease in tail risk, i.e. a higher crisis return. The coefficient of determination, R^2, is a measure of goodness of the "in-sample" fit of the dependent variable. MBV (0.292) shows a better "in-sample" fit than ROA (0.078), ROE (0.194) and PE (0.009).

Table 2: This table presents results from a set of OLS regressions that estimate the relationship between tail risk and prior accounting and market ratios with the regression model:

$$return_i^{crisis} = \beta_0 + \sum \beta_j * variable_i^{pre-crisis}$$

All variables are standardized to have a mean of zero and a standard deviation of one.

Regression Results: Bad bank days

	Dependent variable:							
	Return on bad bank days/ tail risk							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MBV	-0.540***		-0.501***		-0.502***		-0.536***	-0.521***
	(-13.876)		(-12.574)		(-8.048)		(-13.686)	(-7.175)
	[0.292]		[0.253]		[0.122]		[0.286]	[0.099]
ROA		-0.280***	-0.147***					
		(-6.307)	(-3.681)					
		[0.078]	[0.028]					
ROE				-0.441***	-0.048			-0.020
				(-10.622)	(-0.767)			(-0.241)
				[0.194]	[0.001]			[0.000]
PE						0.095*	0.035	0.026
						(2.057)	(0.888)	(0.507)
						[0.009]	[0.002]	[0.001]
Intercept	-0.000	0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	470	470	470	470	470	470	470	470
R^2	0.291	0.078	0.311	0.194	0.292	0.009	0.293	0.293
Adjusted R^2	0.290	0.076	0.309	0.193	0.289	0.007	0.290	0.288

Note: p-values: *p<0.05 **p<0.01 ***p<0.001

t-values in (), partial r^2 in []

In the second step, we look into the multivariate regression with both MBV and ROA/ROE/PE, number (3), (5), (7). Adding the corresponding return variable to the regression with the market-to-book value leads to slight increases in R^2 and adjusted R^2. However, MBV still seems to be the variable that explains more of the dependent variable, since it has a much higher partial R^2, which gives us the percentage of explanation that is explained by one but not the other variable. The high value of partial R^2 for the MBV (0.253) in (3), in contrast to the much lower value for the ROA (0.028), indicates that the explanatory power of the MBV is much stronger compared to the return variable. The same applies for regression (5) with ROE (0.122 for MBV, 0.001 for ROE) and (7) with PE (0.286 for MBV, 0.002 for PE). We also note that the estimates and t-stats remain high for the MBV, while being much lower for the ROA, ROE and PE.

If we regress tail return on MBV, ROE and PE together (number (8)), we get a similar picture. The high significance and partial R^2 of MBV indicates that the explanatory power stems mainly from that value, while both ROE and PE are insignificant.

The high significance of regression (1) leads us to the conclusion that H1 (see section 3) is true. MBV seems to explain a significant part of the variation in tail risk. Looking at (4) and (6) also supports what we have expected: Both, ROE and PE have a significant correlation with tail risk. However, both ratios lose their significance if we add MBV to the regression ((5), (7) and (8)). This leads us to also approve H2a and H2b: ROE and PE do not explain anything that is not already explained in the MBV.

For the logarithmic transformation, we take the natural logarithm of the independent variables above. For the tail risk variable, we exclude any average crisis return which is positive, and take the absolute value before applying logarithms. Although we have 440 numbers of observations after this restriction, this allows us to not perform other transformations, which might skew the results (see table 13 for summary statistics). We do not standardize these variables, since the interpretation would be difficult with standardization and logarithmic transformation.

Table 3: This table presents results from a set of OLS regressions that estimate the relationship between tail risk and prior accounting and market ratios with the regression model:

$$\ln(return_i^{crisis}) = \beta_0 + \sum \beta_j * \ln(variable_i^{pre-crisis})$$

For the logarithmic decomposition, we ignore positive numbers for return on bad bank days in order to apply logarithms.

MV BV Decomposition

	Dependent variable:					
	log return on bad bank days/ tail risk					
	(1)	(2)	(3)	(4)	(5)	(6)
log MBV	1.263^{***}		1.238^{***}		1.261^{***}	
	(11.742)		(8.426)		(11.639)	
	[0.239]		[0.14]		[0.237]	
log ROE		0.530^{***}	0.023			1.261^{***}
		(7.581)	(0.256)			(11.639)
		[0.116]	[0.000]			[0.237]
log PE				-0.131	-0.023	1.238^{***}
				(-1.297)	(-0.256)	(8.426)
				[0.004]	[0.000]	[0.14]
Intercept	-5.167^{***}	-3.004^{***}	-5.098^{***}	-3.749^{***}	-5.098^{***}	-5.098^{***}
	(-53.53)	(-19.341)	(-17.74)	(-12.473)	(-17.741)	(-17.741)
Observations	440	440	440	440	440	440
R^2	0.239	0.116	0.240	0.004	0.240	0.240
Adjusted R^2	0.238	0.114	0.236	0.002	0.236	0.236

Note: p-values: *p<0.05 **p<0.01 ***p<0.001

t-values in (), partial r^2 in []

Looking at table 3, we see, for (1), (2) and (4), a change in sign of the estimate and the t-statistic compared to table 2. Since we take absolute values of tail returns before taking logarithms, the previous negative estimates of the MBV and ROE are now positive. The PE ratio shows a negative estimate, since it was positive. Due to these transformations, we can interpret a 1% increase in the market-to-book value as a resulting 1.3% decrease in the return on bad bank days.

We again see that ROE (1% level) and PE (10% level) are significant alone ((2) and (4)) but lose their significance if we add MBV to the regression ((3) and (5)). We obtain the same low absolute t-stat (0.256 vs. -0.256), reflecting a p-value of 79.8%. Due to the decomposition (section 3.4.4) we know that if the coefficient of MBV in (1) is equal to the coefficients of ROE and PE in (6), ROE and PE together do not explain any variation in tail risk that is not explained by MBV. Hence, we compute the F-value for the joined significance of ROE and PE, by testing the probability for the coefficients of the unrestricted model (6) to equal the coefficient of the restricted model in (1). We again obtain a p-value of 79.8% (F-value = 0.066, df_1 = 437, df_2 = 1), emphasizing that the ROE and PE together do not significantly explain more than the MBV alone. We conclude that the explanatory power from both ROE and PE is included in the MBV. Hence, we cannot reject H3.

Overall, our regressions show what we expected from our theoretical model: Both, ROE and PE explain some of the variation of tail risk. However, together they do not explain more than the MBV alone, giving an indication that the explaining factor might stem from the MBV. In the simple regression, MBV explains around 29% in the variation of tail risk. This means that MBV can, at least, partly serve as a proxy for banks' exposure to systemic risk. Our theoretical model implies a possible mechanism: market participants might have priced possible government bailouts in the share price of banks before the recent financial crisis.

5.2 Robustness tests

We have seen that MBV can explain tail risk and has more explanatory power than ROE and PE. Our robustness test explores if the findings are robust under slightly different assumptions. First, we add control variables, which might be correlated with an institutions' tail risk. Thus, we also explore if the explanatory power of the MBV stems from correlation with another factor. We choose the common accounting ratios and try to link them qualitatively to our theoretical explanation. In specific, we test for the control variables size, book leverage, market leverage, non-interest income, interest income, intangibles, loans, deposits and dividends (see appendix, table 17 for definition of the control variables). Second, we explore the relationship between MBV on tail risk for varying levels of leverage, since our theoretical model predicts an increase in the sensitivity of MBV for higher levered firms. Finally, we re-estimate the main regression using quantile-regression to test whether the results are applicable to other quantiles.

5.2.1 Control variables

Size. We are controlling for size since we expect a negative relationship between size and tail risk. The larger the firm, the more important should it be for the whole financial system. In case of a significant institution, the bad days in the economy could even stem from a drop in the return from that firm, reflected directly in our measure for firm-specific tail risk.

Additionally, large institutions are often "systemically important institutions" and due to their size more interconnected with other banks, which are both reasons why these large firms would expect government guarantees in case of a breakdown. Literature finds that size is a primary factor for explaining systemic risk (Varotto & Zhao, 2018; Laeven et al 2016). Vallascas & Keasey (2012) find that a size cap for firms would decrease systemic risk. Hence, we expect size to be another factor explaining tail risk, since a larger firm is more important for the economy and also more likely to expect government guarantees.

Leverage. Leverage is an important control variable, since a higher leverage changes the risk preference of equityholders due to gambling for resurrection (see also section 2.2.2). Firms with higher leverage would be more likely to take on risk and take higher advantage of government guarantees. We control for both book and market leverage. Book leverage is closely related to regulators measures of capital requirements (i.e. CET 1). However, market leverage includes the market value of equity, which provides us with an indicator of how market equity is valued. The theoretical model shows that the relation of tail risk and MBV is stronger for higher levered firms. Acharya & Franks (2008) show in their model, that low interest rates, due to government guarantees, lead to incentives for firms to have higher leverage. Acharya & Thakor (2016) indicate in their model, that higher leverage would induce banks to choose liquidation, and other literature document the relationship between leverage and banks' balance sheet decision (Adrian & Shin, 2010).

Non-interest and interest income. Non-interest income and interest income are indicators of the banking activities the firm engages in. Whereas interest income is attributed to the traditional deposit taking and lending business of the firm, non-interest income is associated with investment banking, asset management, trading and securitization businesses (Brunnermeier et al 2012). Previous studies have found that a higher share of non-interest income is correlated with a higher systemic risk (Brunnermeier et al 2012) and the predictiveness of the return measure on tail risk is stronger for non-interest income (Meiselman et al, 2018). Meiselman et al (2018) offer a possible explanation by linking the non-interest income to high-risk banking activities outside of the core lending business.

Intangible assets. We further account for intangible assets. The concept of intangible assets is closely related to franchise value, such as firm brand, customer rights or intellectual property leading to future growth opportunities (Chousakos & Gorton, 2017). However, due to accounting standards, not all types of intangible assets are allowed to be recognized on the balance sheet, only if they are purchased or internally developed according to IAS (IAS 38).

We use these book values of intangible assets, which is why we can only proxy for franchise value. Hence, including this control variable allows us to partly separate the effect of government guarantees from the one of franchise value.

Loans and deposits. We add a bank's share of loans and deposits as control variables. Loans alone do not give us an indication about the riskiness of the banks' portfolio, since the latter also depends on other activities, i.e. engagement in trading activities. Similarly, deposits also do not give us an indication of the stability of financing side of banks, since they depend on banks' financing structure. Adrian & Brunnermeier (2016) differentiate between non-interest bearing deposits, which are allocated across banks in case of stress, and interest-bearing deposit, which are more stable sources of funding. In their estimation of CoVaR, non-interest bearing deposits positively and interest-bearing deposits negatively predict future tail risk. However, we do not differentiate between these types of deposit in this set of control variables.

Dividends. We include dividends as a control variable, since Acharya et al (2017) argue that dividend payout policy can exert negative externalities on other banks, thus increasing systemic risk. Meiselman et al (2018) find an empirical relationship between higher dividends and larger tail risk. First, firms with high earnings on equity would issue dividends, since dividend persistence is expected from investors. Second, dividends have a strong signaling power, hence strong future returns on shares are expected. Both of these arguments strengthen our existing relationship between return and tail risk and might be reasons for taking higher systemic risk and taking advantage from government guarantees.

Beta. As another control variable, we add the one-year CAPM-beta (Sharpe, 1964). The measure is different to all other measures used in this thesis. Since we want to find out whether market and book values of banks can give us information about their tail risk, we do not work with modelled and estimated values. Beta, however, is a proxy for co-movement with the market that cannot be directly observed and has to be estimated. We calculate the firms' covariance with the market divided by the variance of the market in the pre-crisis year, as a modelled measure for the firm's co-movement with market returns. We add beta as control variable since it has been showed that the measure can actually explain firms' risk, even though it does not explicitly focus on tail risk. However, using systematic risk to estimate tail risk might not add further explanatory value, since both are measures driven by the performance of the banking sector or market, respectively. If a bank would choose risky projects to increase its earnings and MBV, this would likely lead to higher tail risk and higher systematic risk, measured in a higher beta.

Again, we run the following regression:

$$return_i^{crisis} = \beta_0 + \beta_1 * MBV_i^{pre-crisis} + \sum \beta_j * control_i^{pre-crisis}$$

We run the regression with our tail risk measure, MBV and each of the control variables separately (Table 4 and 5), in random combinations and all together (Table 6), again under standardization, so we can compare the estimates. We obtain the following results: In all separate control regressions, our estimate for market-to-book is still significant at the 5%- level, indicating that the findings are robust.

Table 4: This table presents results from a set of OLS regressions that estimate the relationship between tail risk and MBV and other control variables with the regression model:

$$return_i^{crisis} = \beta_0 + \beta_1 * MBV_i^{pre-crisis} + \sum \beta_j * control_i^{pre-crisis}$$

All variables are standardized to have a mean of zero and a standard deviation of one.

Regression Results

	Dependent variable:				
	Return on bad bank days/ tail risk				
	(1)	(2)	(3)	(4)	(5)
MBV	-0.177***	-0.565***	-0.599***	-0.555***	-0.558***
	(-4.655)	(-14.931)	(-15.238)	(-13.041)	(-14.302)
	[0.046]	[0.331]	[0.34]	[0.274]	[0.312]
Size	-0.643***				
	(-16.961)				
	[0.389]				
Book leverage		-0.206***			
		(-5.429)			
		[0.061]			
Market leverage			-0.174***		
			(-4.433)		
			[0.042]		
Non-Interest Income				-0.009	
				(-0.206)	
				[0.000]	
Interest Income					0.021
					(0.527)
					[0.001]
Intercept	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	454	454	454	454	454
R^2	0.580	0.354	0.341	0.312	0.312
Adjusted R^2	0.578	0.351	0.338	0.309	0.309
Note:			p-values: *p<0.05 **p<0.01 ***p<0.001		

t-values in (), partial r^2 in []

Table 5: This table presents results from a set of OLS regressions that estimate the relationship between tail risk and MBV and other control variables with the regression model:

$$return_i^{crisis} = \beta_0 + \beta_1 * MBV_i^{pre-crisis} + \sum \beta_j * control_i^{pre-crisis}$$

All variables are standardized to have a mean of zero and a standard deviation of one.

Regression Results

	Dependent variable:				
	Return on bad bank days/ tail risk				
	(1)	(2)	(3)	(4)	(5)
MBV	-0.472^{***}	-0.559^{***}	-0.560^{***}	-0.514^{***}	-0.306^{***}
	(-10.918)	(-14.246)	(-14.929)	(-10.812)	(-8.611)
	[0.209]	[0.310]	[0.331]	[0.206]	[0.141]
Intangibles/Assets	-0.186^{***}				
	(-4.301)				
	[0.039]				
Loans/Assets		-0.007			
		(-0.167)			
		[0.000]			
Deposits/Assets			0.229^{***}		
			(6.101)		
			[0.076]		
Dividends/Equity				-0.077	
				(-1.614)	
				[0.006]	
Beta					-0.549^{***}
					(-15.453)
					[0.346]
Intercept	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	454	454	454	454	454
R^2	0.339	0.312	0.364	0.316	0.550
Adjusted R^2	0.336	0.309	0.362	0.313	0.548

Note: p-values: *p<0.05 **p<0.01 ***p<0.001

t-values in (), partial R^2 in []

Table 6: This table presents results from a set of OLS regressions that estimate the relationshi between tail risk and MBV and other control variables with the regression model:

$$return_i^{crisis} = \beta_0 + \beta_1 * MBV_i^{pre-crisis} + \sum \beta_j * control_i^{pre-crisis}$$

All variables are standardized to have a mean of zero and a standard deviation of one.

Regression Results

	Dependent variable:						
	Return on bad bank days/ tail risk						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MBV	-0.129**	-0.556***	-0.499***	-0.560***	-0.073*	-0.571***	-0.112**
	(-3.011)	(-13.04)	(-11.859)	(-11.611)	(-1.971)	(-13.097)	(-2.419)
	[0.02]	[0.274]	[0.239]	[0.231]	[0.009]	[0.276]	[0.013]
Size	-0.666***				-0.519***		-0.532***
	(-15.812)				(-13.098)		(-13.096)
	[0.358]				[0.277]		[0.280]
Book leverage	-0.113			-0.203***			0.104
	(-1.701)			(-5.174)			(0.853)
	[0.006]			[0.056]			[0.002]
Market leverage	0.163*				0.012	-0.021	0.008
	(2.390)				(0.388)	(-0.386)	(0.112)
	[0.013]				[0.000]	[0.000]	[0.000]
Non-Interest Income		-0.007		0.013		0.015	0.073*
		(-0.166)		(0.317)		(0.362)	(2.382)
		[0.000]		[0.000]		[0.000]	[0.013]
Interest Income		0.020			-0.064*		-0.060*
		(0.512)			(-2.324)		(-1.775)
		[0.000]			[0.012]		[0.007]
Intangibles/ Assets			-0.146***				-0.051
			(-3.428)				(-1.425)
			[0.026]				[0.005]
Loans/ Assets			-0.071				-0.085**
			(-1.862)				(-2.635)
			[0.008]				[0.015]
Deposits/ Assets			0.220***			0.216***	0.161**
			(5.701)			(4.093)	(2.012)
			[0.068]			[0.036]	[0.009]
Dividends/ Equity				-0.019			0.057
				(-0.369)			(1.708)
				[0.000]			[0.007]
Beta					-0.381***		-0.376***
					(-11.883)		(-12.014)
					[0.240]		[0.25]
Intercept	0.000	0.000	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	454	454	454	454	454	454	454
R^2	0.586	0.312	0.384	0.354	0.690	0.365	0.714
Adjusted R^2	0.582	0.308	0.379	0.350	0.687	0.359	0.707

Note: p-values: $^{*}p<0.05$ $^{**}p<0.01$ $^{***}p<0.00$

t-values in (), partial r^2 in []

Looking closer at the controls, we find significant estimates for size, book as well as market leverage, intangible assets, deposits and beta. The estimate for size has a negative sign and is highly significant, confirming our argumentation that larger firms tend to be more systemically relevant and experience greater losses on crisis days. Both book and market leverage show a negative coefficient. Hence, leverage indeed is a factor contributing to higher tail risk. We further find that intangible assets show a significant negative relationship with tail risk. Furthermore, we find a positive significant relationship between the share of deposits and tail risk, hence higher deposits lead to lower tail risk, i.e. higher returns in crisis times. We also observe a negative relationship between beta and tail risk. A higher beta is, therefore, a sign for greater losses in crisis times. This is interesting since it means that, even though focusing on general market co-movements, beta can still explain returns in extremely bad times.

We do not find consistent significant estimates for the remaining variables at the 5%-level. Looking at tables 4 and 5, which show regressions of MBV together with only one control variable, we see that its coefficient experiences the largest decrease in estimate and t-value when regressed together with size and beta. Hence, size and market co-movement of a firm seem to explain part of the variation of tail risk, which is explained by MBV if it serves as the only explanatory variable. However, in tables 4-6, we observe that the market-to-book value is still significant at the 5%-level and consistently shows a negative coefficient in all regressions, indicating that our findings from section 5.1 are robust.

5.2.2 Results under varying leverage

Since leverage is a much discussed factor in banking literature and our theoretical model also predicts a relation with the MBV, we further explore these two variables by dividing the sample into quartiles depending on their book leverage: 25% is the smallest quartile and 100% is the largest quartile. In table 7, we run the regression with MBV and book leverage.

Table 7: This table presents results from a set of OLS regressions that estimate the relationship of MBV and leverage on tail risk, after dividing the sample into quartiles depending on their leverage:

$$return_i^{crisis} = \beta_0 + \beta_1 * MBV_i^{pre-crisis} + \sum \beta_2 * leverage_i^{pre-crisis}$$

All variables are standardized to have a mean of zero and a standard deviation of one.

Regression Results: Varying leverage

	Dependent variable:			
	Return on bad bank days/ tail risk			
	25%-Quartile	50%-Quartile	75%-Quartile	100%-Quartile
MBV	-0.508***	-0.691***	-0.584***	-0.519***
	(-7.093)	(-8.713)	(-7.376)	(-7.002)
	[0.312]	[0.408]	[0.331]	[0.306]
Book leverage	-0.282	0.233	-0.607*	-0.144
	(-1.166)	(0.616)	(-1.69)	(-1.178)
	[0.012]	[0.003]	[0.025]	[0.012]
Intercept	-0.059	0.091	0.181*	-0.120
	(-0.213)	(0.517)	(1.747)	(-0.638)
Observations	114	113	113	114
R^2	0.316	0.409	0.337	0.308
Adjusted R^2	0.303	0.399	0.325	0.295
Note:				p-values: *p<0.05 **p<0.01 ***p<0.001

t-values in (), partial r^2 in []

Since book leverage is not significant in these regressions except for the 75%-quartile, we cannot make profound statements about leverage changes within these quartiles. We observe a much stronger relationship for the MBV in the 50%-quartile with an estimate of -0.691 for the standardized variables, but we do not find a general trend if higher leverage predicts a higher significance or estimate for the MBV. Hence, we cannot confirm the impact of leverage on the correlation of MBV and tail risk as indicated by the theoretical model in section 3.

5.2.3 Results under varying size

Since size has a big impact on the coefficient and t-value of MBV if added to the regression (see table 4), we further study the relationship between size and MBV by regressing after dividing the sample into size quartiles as we did with leverage before. We run the regressions with MBV as well as with MBV and size to further explore the relations between size and MBV on tail risk.

Table 8: This table presents results from a set of OLS regressions that estimate the relationship of MBV (and size) on tail risk, after dividing the sample into quartiles depending on their size:

$$return_i^{crisis} = \beta_0 + \beta_1 * MBV_i^{pre-crisis} + \sum \beta_2 * size_i^{pre-crisis}$$

All variables are standardized to have a mean of zero and a standard deviation of one.

Regression Results: Varying size

	Dependent variable:							
	Return on bad bank days/ tail risk							
	25%-Quartile	50%-Quartile	75%-Quartile	100%-Quartile	25%-Quartile	50%-Quartile	75%-Quartile	100%-Quartile
MBV	0.129	-0.357***	-0.485***	-0.106	0.131	-0.342***	-0.380***	-0.008
	(1.322)	(-5.049)	(-6.787)	(-1.743)	(1.289)	(-4.858)	(-5.46)	(-0.132)
	[0.015]	[0.187]	[0.293]	[0.026]	[0.015]	[0.177]	[0.213]	[0.000]
Size					-0.014	-0.779	-1.337***	-0.361***
					(-0.076)	(-1.884)	(-4.597)	(-4.561)
					[0.000]	[0.031]	[0.161]	[0.158]
Intercept	0.917***	0.442***	-0.197***	-1.024***	0.904***	0.104	-0.083	-0.621***
	(11.854)	(8.428)	(-3.469)	(-11.412)	(5.028)	(0.554)	(-1.434)	(-5.125)
Observations	114	113	113	114	114	113	113	114
R^2	0.015	0.187	0.293	0.026	0.015	0.212	0.407	0.180
Adjusted R^2	0.007	0.179	0.287	0.018	-0.002	0.198	0.396	0.165

Note: p-values: $^{*}p<0.05$ $^{**}p<0.01$ $^{***}p<0.001$

t-values in (), partial r^2 in []

In table 8, we find that MBV seems to have the most explanatory power in both estimates and t-values for the middle quartiles (50% and 75%), and is much less significant for extreme size values. Interestingly, the size factor has a higher explanatory power for the higher quartiles (75% and 100%), but much less explanatory power in the lower quartiles. In the highest quartile, we observe a large drop in significance and estimate of the MBV when adding size, which is much more significant. Since MBV increase with size (Kane, 2014), which is confirmed in our own data sample (see appendix table 14), one possible hypothesis could be that for large firms, such as firms that are "too big to fail", the firm size incorporates some information otherwise given through the MBV. This would mean that size, especially for large firms, partly could be related to government guarantees, as indicated by studies of Gandhi & Lustig, 2015 and Acharya et al, 2016a.

5.2.4 Quantile regression

Lastly, we perform a robustness test by using quantile regression for the standard regression using market-to-book value. Quantile regressions incorporate estimates for both conditional mean and conditional volatilities, hence this method does not require the distributional assumptions of OLS to be an efficient estimator and serves as an additional robustness check. Also, by estimating the median and other quantiles the results are less sensitive to outliers than by estimating the mean.

We obtain the following findings:

Table 9: This table presents results from quantile regression to estimate the relationship between tail risk and MBV.
All variables are standardized to have a mean of zero and a standard deviation of one.

Quantile regression

	Dependent variable:					
	Return on bad bank days/ tail risk					
	OLS	*Quantile regression*				
		(5%)	(25%)	(50%)	(75%)	(95%)
MBV	-0.540***	-0.421***	-0.689***	-0.721***	-0.488***	-0.386***
	(-13.876)	(-4.005)	(-11.239)	(-11.134)	(-8.507)	(-9.923)
Intercept	-0.000	-1.580***	-0.528***	0.076	0.629***	1.179***
	(0.000)	(-13.376)	(-8.67)	(1.416)	(13.742)	(22.030)
Observations	470	470	470	470	470	470

Note: p-values: $^{*}p<0.05$ $^{**}p<0.01$ $^{***}p<0.001$
t-values in ()

In table 9, we find significant (0.1% level) and negative estimates for the market-to-book values in all regressions. We see that the regression has higher significance in the median and 25%-quantile than in the peripheral quantiles. In conclusion we find that regression is not only significant and negative in the mean but also in other quantiles.

Overall, our robustness test show that MBV is a significant factor after accounting for other control variables, different leverage levels or different quantiles. Regardless of which control variables we include, MBV has a significant impact on tail risk. This is a strong sign that MBV has an explanatory power that does not come from its correlation with other relevant variables. Besides MBV, we find highly significant control variables in size, book as well as market leverage, intangible assets, deposits and beta, with especially high coefficients and t-values for beta and size. As further robustness test, we re-sample the original data according to leverage and size, finding that while MBV as a factor is still significant across different leverage levels, MBV seems to be less significant when looking at the lowest and the highest size quartile.

We also find that our findings are significant by using quantile regression, estimating other quantiles than the mean.

As an interesting finding, we find an R^2 of over 70% when adding all control variables, which indicates that other bank ratios can also explain part of the variation in tail risk. In our next step, we try to use these other variables, besides MBV, to develop a model allowing us to estimate tail risks in an out-of-sample application.

5.3 Estimation of tail risk

We have seen that MBV and several other variables show significant correlation with banks' tail risk. In this final part, we try to make a comparison about the estimated tail risk measures in 2006 and 2016. Hence, we will use these findings to build a model with the estimates for the recent financial crisis to estimate the current tail risk banks are exposed to.

Unlike before we will not standardize the variables. First, we again run the OLS regression in the following style:

$$return_i^{crisis} = \beta_0 + \sum \beta_j * variable_i^{pre-crisis}$$

Since including a large amount of variables leads to higher variance and could lead to overfitting, we apply two methods for model selection: machine learning (LASSO) and model selection using AIC in a stepwise algorithm. The least absolute shrinkage and selection operator (LASSO) is a regression analysis method that can be applied to variable selection by introducing a penalty-term λ for each included variable (Tibshirani, 1996). We can apply cross-validation to find the optimal penalty-term λ, which is a method aiming to minimize the residual sum of squares.

Our second method model selection using the Akaike Information Criterion (AIC) aims at minimizing information loss (Akaike, 1973), by adding variables to the existing model if the combined model shows a lower AIC than the previous model.

Since both models suggest a different number of variables, they produce different results. Table 9 shows the coefficients, t-values and partial R^2 of the coefficients of both models. We do not standardize the coefficients for these regressions, as we apply these to a different sample later. Similar to tables (4) - (6), the most significant variables are still MBV, size and ROE.

To differentiate between the models, we include some metrics for comparing both models in table 10. We find that the AIC model is a better model in terms of AIC, R^2, adj. R^2, SSR than the LASSO model. However, the LASSO model is better in terms of BIC and has less variables. Hence, we will use both models for the estimation.

Table 10: This table presents both models from the AIC and LASSO model selection, after been chosen in the following style:

$$return_i^{crisis} = \beta_0 + \sum \beta_j * variable_i^{pre-crisis}$$

Regression Results: AIC vs LASSO model

	Dependent variable:	
	Return on bad bank days/ tail risk	
	Lasso-Model	AIC-Model
MBV	-0.003***	-0.005***
	(-3.994)	(-5.224)
	[0.034]	[0.058]
Size	-0.008***	-0.008***
	(-17.713)	(-16.403)
	[0.412]	[0.377]
Non-Interest	0.242**	0.157*
Income	(3.249)	(2.009)
	[0.023]	[0.009]
ROE		0.044***
		(3.387)
		[0.025]
Interest Income	-0.168*	-0.156
	(-2.2)	(-1.576)
	[0.011]	[0.006]
Loans/	-0.010*	-0.009
Assets	(-2.061)	(-1.836)
	[0.009]	[0.008]
Intangibles/	-0.054*	-0.068*
Assets	(-2.049)	(2.538)
	[0.009]	[0.014]
ROA		-0.180
		(-1.63)
		[0.006]
Intercept	0.060***	0.066***
	(11.816)	(12.072)
Observations	454	454
R^2	0.612	0.622
Adjusted R^2	0.607	0.615
Note:		p-values: $^{*}p<0.05$ $^{**}p<0.01$ $^{***}p<0.001$

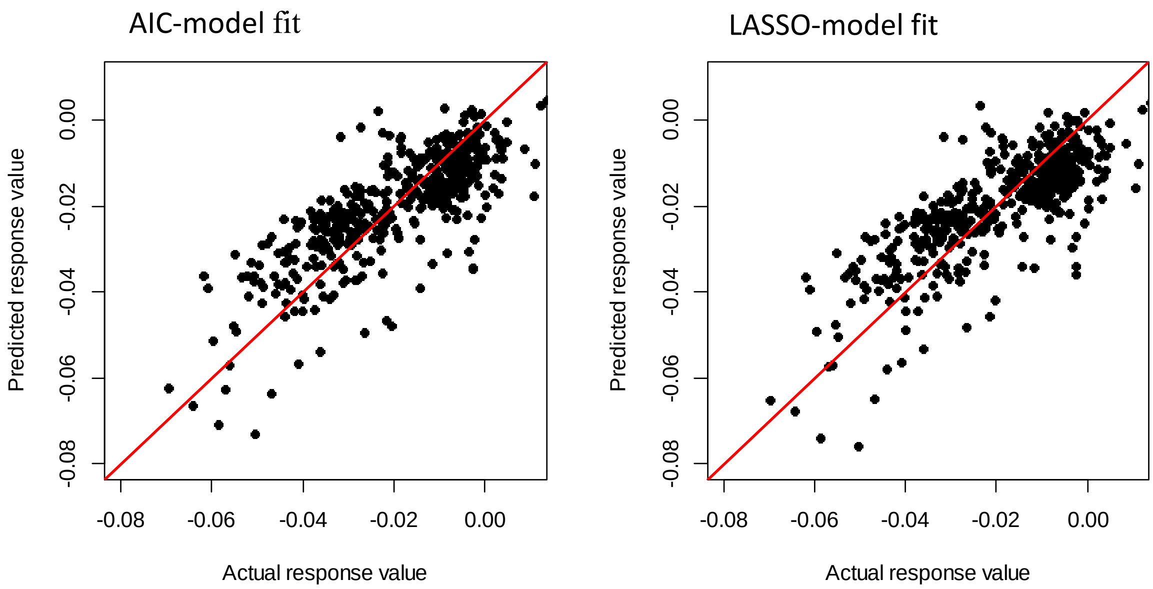
t-values in (), partial r^2 in []

Table 11: This table presents the different comparison metrics: Akaike Information Criterion, Bayesian Information Criterion, coefficient of determination (R^2), adjusted coefficient of determination (adj. R^2) and the sum of squared residuals for the LASSO and the AIC model.

	AIC	BIC	RSQ	RSQ adj	SSR
lasso_model	-2883,18	-2850,23	0,612	0,607	0,045
AIC_model	-2890,75	-2849,57	0,622	0,615	0,044

The first important observation is the relatively high R^2 of over 60%. This means that with the measures we have identified to be relevant for tail risk, in 2006 we can explain more than half of the variation in losses on bad days during the financial crisis. We test the model fit by testing the in-sample fit and we plot the actual response values (tail risk) against the predicted models (constructed tail risk) in Figure 1. We find a close approximation of the values towards the bisecting line in both plots, which shows that the predicted values are very close to the actual values of tail risk.

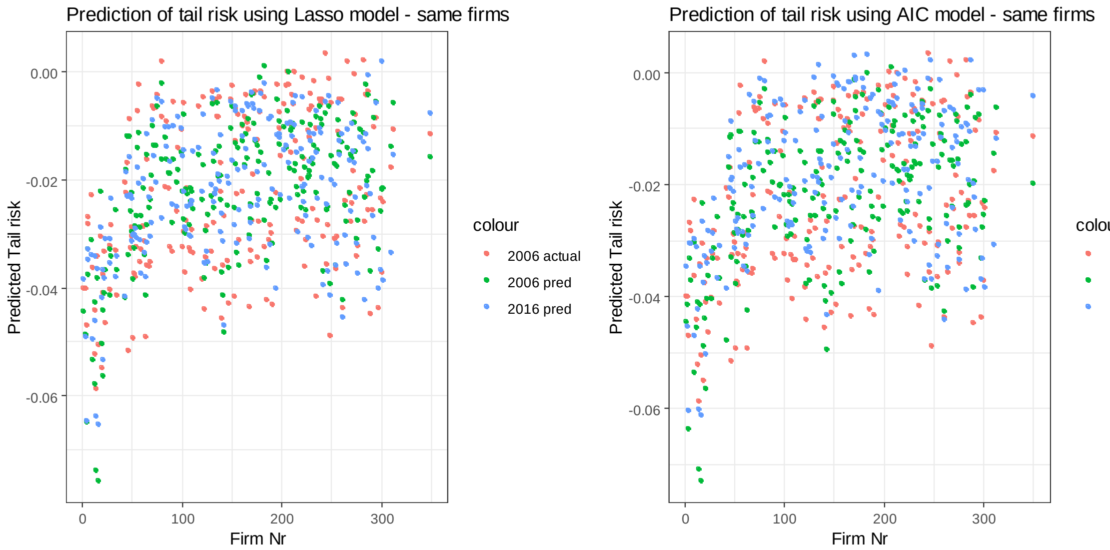
Figure 1: This figure plots the 2006 predicted tail risk variable against the 2006 measured tail risk variable for the AIC model and the LASSO model.



In the next step, we estimate the "potential tail risk" in 2016[1]. Since the firms used in the original regression form 2006 do not exactly match the firms from 2016 due to bankruptcy or M&A, we only find 209 firms in 2016, which still exist under the same PERMCO than in 2006. We compare the estimation of the AIC and the LASSO model of these firms, which stayed the same during both 2006 and 2016, in figure 2.

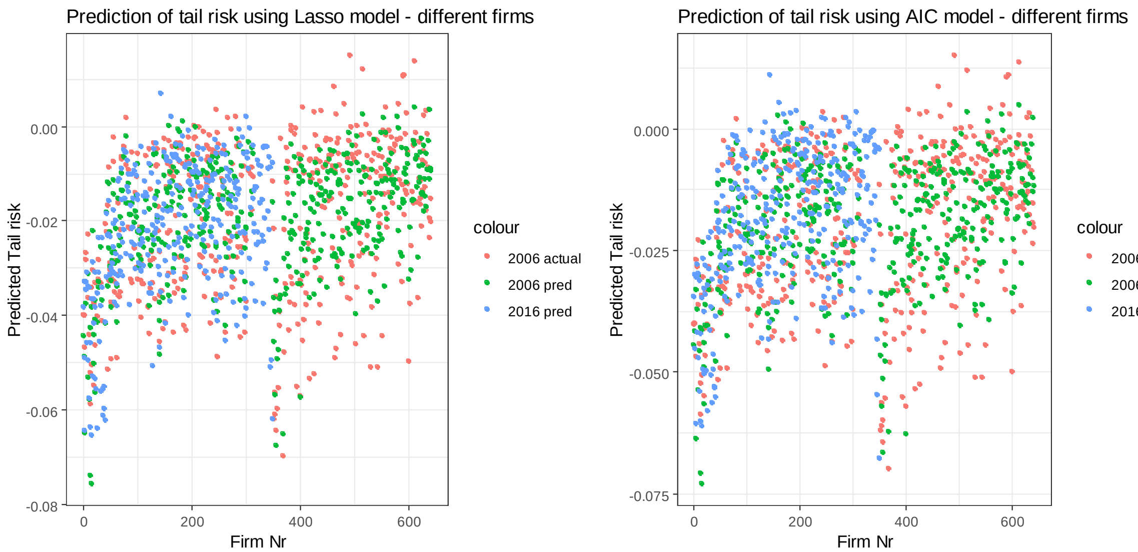
[1] We take the values from 2016 to have a greater size of firms. We have a smaller sample size in 2017 since some firms might not yet have filled in their reports.

Figure 2: This figure shows the scatterplot for the actual tail risk measure in 2016 and predicted tail risk measure in 2006 and 2016. On the left side is the prediction using the LASSO-model, on the right side is the prediction using the AIC-model. The figure entails the 209 firms which operated and filled in their SEC reports in both 2006 and 2016.



Since this sample suffers from survivorship bias and has much less observations than the original regression, we add all available firms in 2006 and 2016 to the plot in figure 2 for a view on the whole banking sector, giving us 454 observations in 2006 and 325 observations in 2016.

Figure 3: This figure shows the scatterplot for the actual tail risk measure in 2016 and estimated tail risk measure in 2006 and 2016. On the left side is the prediction using the LASSO-model, on the right side is the estimation using the AIC-model. The figures entail the 454 firms for 2006 and 325 firms for 2016.



For robustness, we plot the predicted values for 2006 and 2016 of all available firms (figure 3). First, we do not estimate higher or lower tail risk measures for firms that disappeared in the financial crisis or after, compared to the ones still existing. Second, even after including firms which newly emerged, we do not find a specific difference in 2006 and 2016 tail risk estimations. Additionally, we plot the histograms for the estimated values for tail risk in 2006 vs. 2016 with both models in figure 7 (see appendix). We find a slightly more stable histogram with less fat tails in 2016 compared to 2006. However, this could also be due to the fact that in 2016, we have less firms.

This means that the potential tail risk posed by the individual banks would be still high in 2016, when estimated using our model with market and accounting data. Since we cannot compare the estimates of our model, as they are not standardized, we look into the summary statistics of the 2006 (appendix table 15) vs. the 2016 (appendix table 16) sample for comparison. We see a decrease in the mean of the MBV from 2.31 to 1.9 from the 2006 to the 2016 sample. Also, we observe a decrease in the mean value of ROE. However, another significant value is the size factor, which increased in its mean from 7.34 to 8.38 from 2006 to 2016. Interestingly, our findings observe little change in the tail risk of the individual banks. Whereas some variables like ROE and MBV decreased in its mean, leading to lower tail risk, other variables like size increased in its mean, leading to higher tail risk.

Applying our findings from the section 3, this would mean that banks in 2016 rely less on future government guarantees that are priced by investors. The increase in the size of banks, however, leaves questions open. The higher firm size compared to 2006 results in risk levels in 2016 similar to before the crisis, even though MBV decreased on average.

Although we find no or little changes in tail risk of banks in their pre- vs. post-crisis levels (consistent with findings of Sarin & Summers, 2016), we are hesitant in interpretation of our tail risk estimation as this application faces many limitations due to its many assumptions. The most prominent one is the assumption that the estimates from the 2006 regression do not change in their explanatory power until 2016. There might be different possible qualitative explanations why market behavior should have changed, which might have an effect on the relationship of MBV and other variables on tail risk. Further research in this field could increase our understanding.

To sum up, we have seen that we can explain more than 60% of the variation in returns on bad days in the recent financial crisis using the most significant measures out of the relevant measures identified in section 5.2. Even if this prediction again confirms the importance of MBV for tail risk, it shows that we also have to take into account other measures, especially the size of the firm. Looking at our predicted levels for tail risk, we find that, based on the levels of 2016, banks would still experience similar losses on the worst days, given a crisis happened after 2016, which is similar to the one that started in 2007.

6. Discussion and conclusion

The goal of this thesis was to investigate whether market participants considered possible government guarantees when valuing banks' market values before the recent financial crisis and, if yes, how this helps us to get information about the current exposure of certain institutions to systemic risk. Using a theoretical model, we showed that the market-to-book value of a bank should be higher the higher its tail risk, given anticipated government guarantees are priced in the market value of equity. If such bailouts guarantee a minimum return of the risk-free rate to debtholders in case of a systemic breakdown, they lead to an increase in expected return of risky projects and, hence, to an increase in banks' MBV. Therefore, such projects are executed more often, leading to higher returns in normal times, but also to higher losses in bad times.

We use this model to test whether anticipated government guarantees were priced in the market value of equity in 2006. We do this running several regressions. First of all, we investigate the following hypothesis:

H1: *There is a negative relationship between the market-to-book value in normal times and returns on bad days.*

We show a highly significant negative correlation between banks' MBV in 2006 and their losses on the worst days during the crisis (as a proxy for tail risk). Especially mentionable is the relatively high R^2 of over 29%. This could be interpreted as a sign that market participants have considered anticipated government guarantees in banks' market value of equity in 2006.

Since market-to-book value can be decomposed into ROE and PE-ratio, we strengthen our result by testing the following hypotheses:

H2a: *Return on equity does not explain any variation in tail risk that cannot be explained with the market-to-book value.*

H2b: *Price-earnings-ratio does not explain any variation in tail risk that cannot be explained with the market-to-book value.*

H3: *Return on equity and price-earnings ratio together do not contain any information that is not contained in the market-to-book value.*

Even though we also find a significant correlation between banks' ROE, PE-ratio in 2006 and their losses during the crisis, the variables explain less in variation and become insignificant if regressed on tail risk together with MBV. Hence, the size of market-to-book value seems to be an indicator for a bank's exposure to systemic risk.

In order to further investigate the explanatory power of MBV with respect to tail risk, we looked at other variables being mentioned in literature as indicators for banks' systemic risk exposure. Overall, our robustness tests show that MBV is a significant factor after accounting for other control variables, different leverage/size levels or the estimation of different quantiles. Still, the estimate of MBV seems to be less significant for especially small or large firms.

However, other variables, next to MBV, seem to be significantly correlated with banks' tail risk as well. We find that size, leverage, deposits and intangibles are significant indicators for an institution's exposure to systemic risk. In our final part, we try to estimate tail risk levels in 2016 using a fitted model from 2006, which gives similar levels of tail risk than in the original sample, under the condition that using the same estimates is reasonable.

Since tail risk cannot be measured but only proxied, our approach faces limitations since the measure depends on the reliability of the marginal expected shortfall to proxy tail risk. Also, from looking only at one crisis in the US, our results might not be robust. By looking at the MBV as a contributor of risk in the banking sector using other prevailing methods and by testing it in other markets, the results could be strengthened. Our approach using market value-based ratios to estimate risk of the banking sector faces more limitations, since it relies on the investors' beliefs about future cash flows. As an estimator, it can only measure potential tail risk under the assumption that investors keep pricing the MBV according to tail risk, i.e. closely related to the "efficient market assumption". Our estimation also faces more constraints, since we find that even though MBV decreased from 2006 to 2016, an increase in other factors, such as size, might still keep tail risk levels high. The relationship of these other significant variables on tail risk and if this is connected to anticipated government guarantees could be an interesting expansion of our thesis. Furthermore, our assumption for estimating the out-of-sample tail risk is, that the contribution of every variable, i.e. estimate, is the same in 2016 as in 2006, which might not hold. Lastly, we cannot show with certainty that the correlation of MBV with tail risk in our empirical study is attributable to anticipated government guarantees, which the findings from the theoretical model imply.

Our results show, once again, that the financial sector behaves differently than other industries, since our findings about the MBV have different implications than the ones of Fama & French (1992) and Zhang (2005), for the non-financial sector. Furthermore, our findings have interesting implications on previous literature. Existing research on the decrease of the MBV in the banking sector after the financial crisis concluded that heavy regulation through increased capital requirements lead to a damage in the business models of banks (Sarin & Summers, 2016; Chousakos & Gorton, 2017). With our findings, however, we imply that the high MBV can be attributed to high risk levels banks were taking before the financial crisis. Hence, a decrease in the MBV after the financial crisis due to regulations could be a signal for lower systemic risk exposure, rather than a weakening of business models. A possible hypothesis would be that pre-crisis MBV mainly reflected risk-taking behavior through incorporating implicit government guarantees (Atkeson et al, 2018), which might be less pronounced after the crisis.

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8. Appendix

Figure 4: The plot shows the historical development of the market-to-book value of the financial sector from Jan 1976 to Dec 2016. Data is taken from CRSP accessed through WRDS. The ratio is calculated as the sum of the market value of equity divided by the sum of the book value of equity of all banks in our sample at year end.

Figure 5: The plot shows the historical development of the average return on equity per year of the banks in our sample from Jan 1976 to Dec 2016. Data is taken from CRSP accessed through WRDS.

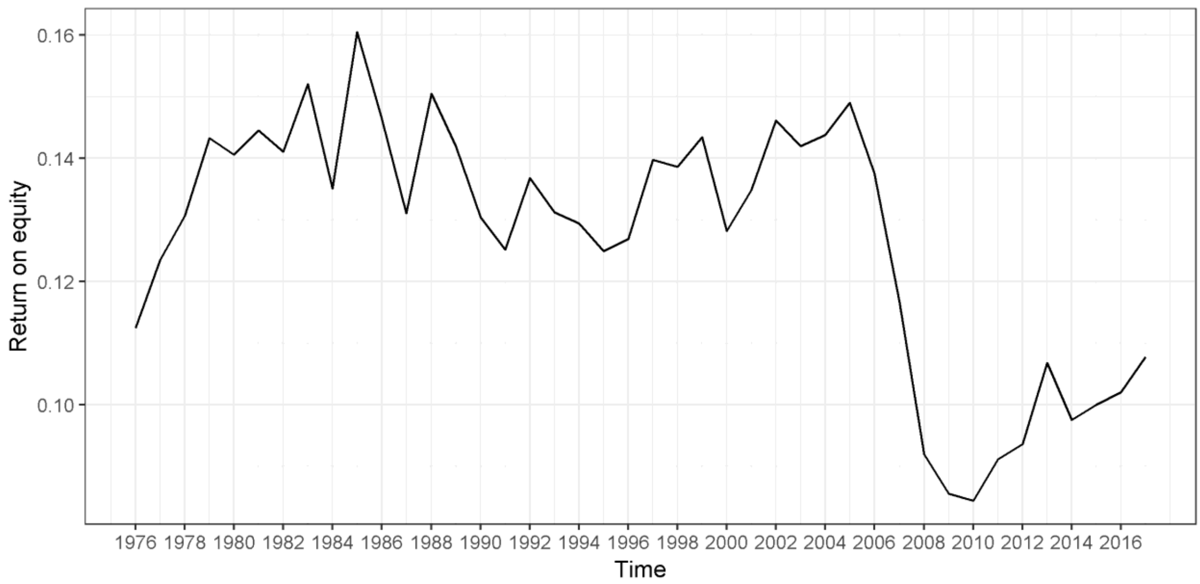

Figure 6: The plot shows the historical development of the average PE-ratio per year of the banks in our sample from Jan 1976 to Dec 2016. Data is taken from CRSP accessed through WRDS.

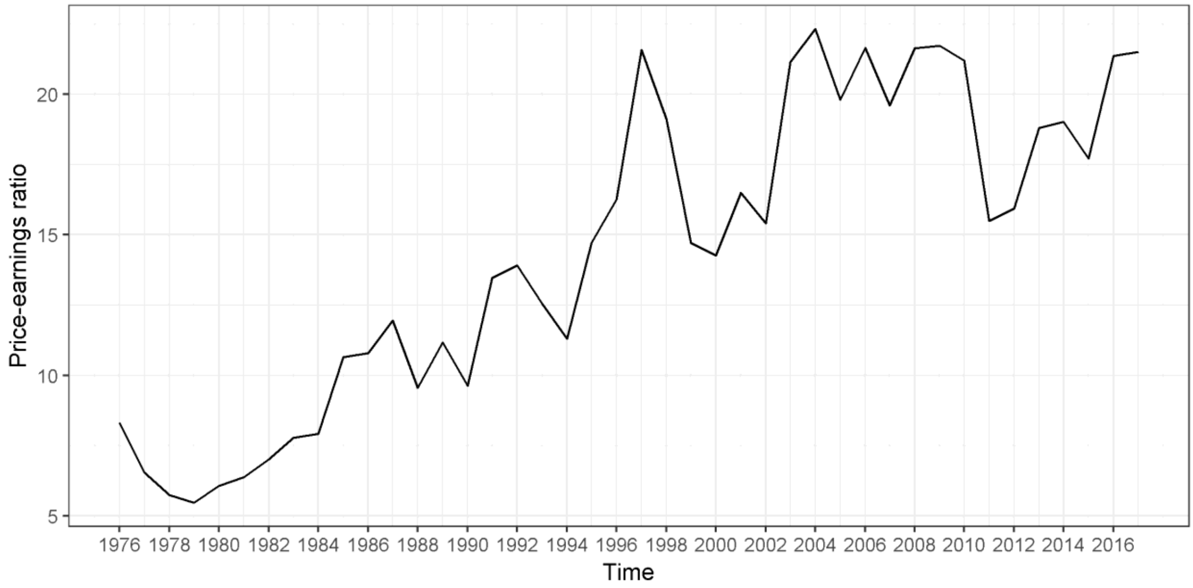

Figure 7: This figure shows the histograms for the tail risk values in 2006 and 2016 for the estimated values using the AIC and the LASSO model. The figures entail the 454 firms for 2006 and 325 firms for 2016.

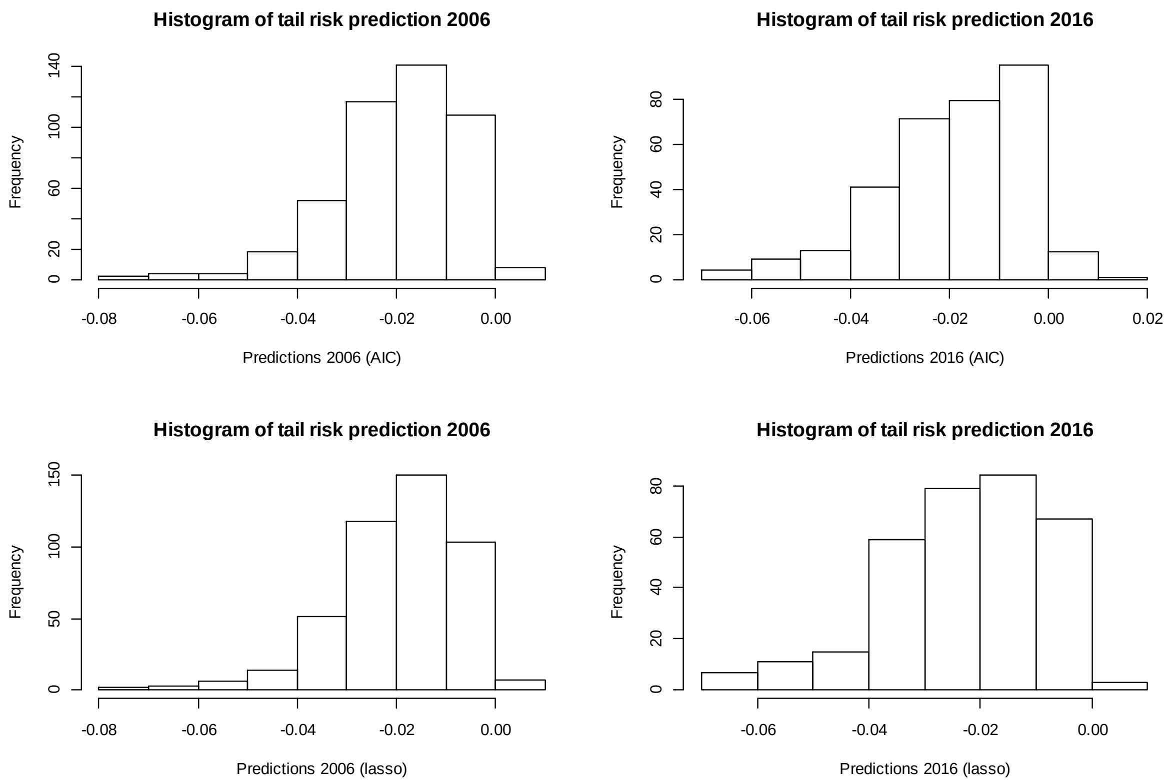

Table 12: This table presents results from a set of OLS regressions that estimate the relationship between tail risk and prior accounting and market ratios with the regression model:

$$return_i^{crisis} = \beta_0 + \sum \beta_j * variable_i^{pre-crisis}$$

The variable for tail risk is calculated using the average returns on the 5% worst days of the whole market. All variables are standardized to have a mean of zero and a standard deviation to one.

Regression Results: Bad market days

	Dependent variable:							
	Return on bad market days/ tail risk							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MBV	-0.504^{***}		-0.467^{***}		-0.487^{***}		-0.501^{***}	-0.506^{**}
	(-12.616)		(-11.395)		(-7.595)		(-12.463)	(-6.78)
	[0.254]		[0.218]		[0.11]		[0.25]	[0.009]
ROA		-0.265^{***}	-0.142^{***}					
		(-5.940)	(-3.459)					
		[0.07]	[0.025]					
ROE				-0.403^{***}	-0.022			0.005
				(-9.504)	(-0.348)			(0.049)
				[0.162]	[0.000]			[0.000]
PE						0.080^{*}	0.024	0.026
						(1.732)	(0.601)	(0.006)
						[0.006]	[0.001]	[0.000]
Intercept	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	469	469	469	469	469	469	469	469
R^2	0.254	0.070	0.273	0.162	0.254	0.006	0.255	0.255
Adjusted R^2	0.253	0.068	0.270	0.160	0.251	0.004	0.252	0.250

Note: p-values: $^{*}p<0.05$ $^{**}p<0.01$ $^{***}p<0.00$

t-values in (), partial r^2 in []

Table 13: In this table we show the summary statistics after applying logarithmic transformation on the variables. We apply logarithms on all variables, after truncating positive outliers for return on bad bank days (tail risk). The rest follows table 1.

Summary statistics: logarithmic values

Statistic	N	Mean	St. Dev.	Min	Max
Return on bad bank days (%)	440	-4.13	0.96	-7.65	-2.66
Equity (billions)	440	5.03	1.38	2.66	10.93
Assets (billions)	440	7.61	1.51	4.65	14.19
Return on Assets (%)	440	-3.21	0.19	-3.90	-2.53
Return on Equity (%)	440	-2.13	0.62	-4.49	-0.24
Market-to-book value	440	0.82	0.37	-0.21	2.18
Price-earnings ratio	440	2.95	0.45	1.58	4.86

Table 14: This table presents results from a set of OLS regressions that estimate the relationship between MBV and size with the regression model, after dividing the initial sample into size quartiles:

$$MBV_i^{pre-crisis} = \beta_0 + \beta_1 * size_i^{pre-crisis}$$

All variables are standardized to have a mean of zero and a standard deviation of one.

Regression Results

	Dependent variable:			
	MBV			
	25%-Quartile	50%-Quartile	75%-Quartile	100%-Quartile
Size	0.473^{**}	0.672	1.371^{***}	0.472^{***}
	(2.918)	(1.214)	(3.659)	(4.06)
	[0.071]	[0.013]	[0.108]	[0.128]
Intercept	-0.177	-0.014	0.028	0.164
	(-1.06)	(-0.054)	(0.352)	(0.863)
Observations	114	113	113	114
R^2	0.071	0.013	0.108	0.128
Adjusted R^2	0.062	0.004	0.100	0.121
Note:				p-values: $^{*}p<0.05$ $^{**}p<0.01$ $^{***}p<0.001$

t-values in (), partial r^2 in []

Table 15: In this table we show the summary statistics of key variables used for the estimation in 2006. The construction of the variables is explained in table 17.

Summary statistics: 2006 AIC/ LASSO estimation

Statistic	N	Mean	St. Dev.	Min	Max
Return on bad bank days (%)	454	-1.95	1.60	-6.98	1.52
ROA (in %)	454	4.02	0.74	2.02	7.93
ROE (in %)	454	12.72	7.57	1.13	78.68
MBV	454	2.31	0.96	0.81	8.84
PE	454	23.32	17.67	8.83	144.63
Size	454	7.34	1.42	4.65	14.19
Book leverage (in %)	454	14.23	8.66	0.00	49.47
Market leverage (in %)	454	42.26	19.04	0.00	87.50
Non-interest income (in %)	454	0.95	0.73	0.03	5.15
Interest income (in %)	454	5.88	0.78	3.37	9.33
Loans/Assets (in %)	454	70.51	12.23	7.95	93.62
Deposits/Assets (in %)	454	74.21	8.95	42.84	89.90
Intangibles/Assets (in %)	454	1.74	2.20	0.00	15.97
Dividends/Assets (in %)	454	4.52	3.97	0.00	38.16
Predicted tail risk (AIC)	454	-0.019	0.013	-0.073	0.005
Predicted tail risk (LASSO)	454	-0.019	0.013	-0.076	0.004

Table 16: In this table we show the summary statistics of key variables used for the estimation in 2016. The construction of the variables is explained in table 17.

Summary statistics: 2016 AIC/ LASSO estimation

Statistic	N	Mean	St. Dev.	Min	Max
ROA (in %)	325	1.71	0.84	0.39	10.77
ROE (in %)	325	10.01	4.06	1.15	27.49
MBV	325	1.90	0.74	0.002	4.85
PE	325	21.71	12.88	0.03	95.98
Size	325	8.38	1.82	5.68	14.73
Book leverage (in %)	325	9.81	6.43	0.00	47.70
Market leverage (in %)	325	35.88	19.67	0.00	99.91
Non-interest income (in %)	325	0.96	0.68	0.06	7.06
Interest income (in %)	325	3.47	0.99	1.07	14.95
Loans/Assets (in %)	325	69.50	11.93	19.03	91.15
Deposits/Assets (in %)	325	77.49	7.98	38.91	91.22
Intangibles/Assets (in %)	325	1.60	1.62	0.00	10.11
Dividends/Assets (in %)	325	3.21	2.54	0.00	17.21
Predicted tail risk (AIC)	325	-0.019	0.015	-0.068	0.011
Predicted tail risk (LASSO)	325	-0.022	0.014	-0.065	0.007

Example 1: We show that in a setting with government guarantees we will obtain a MBV larger than 1 in a state with government guarantees:

$$(13)\ M = \frac{1}{R^f} \times (1 - q_c) \times \left[\left(R^n - \boldsymbol{\rho} \times \boldsymbol{R^f} \right) \times I - N + M \right] > N$$

$R^f = 1.02$

$R^n = 1.03$

$q_c = 0.03$

$\rho = 0.8$

By plugging these numbers in equation (13) above, we get

$$M = 1.018 \times \left[0.951 \times \frac{N}{0.1} - N + M \right]$$

And simplified:

$$M = 1.358 \times N$$

Table 17: In this table we present the computation of the variables. We obtain all variables from the Wharton Research Database Services (WRDS) from the CRSP for daily stock market data and the joined CRSP/Compustat database for bank annual data.

Variable name	**Definition**	**Data description** (CRSP, Compustat)
MBV	Market capitalization over tangible book value of equity	$\frac{prc \times shrout}{ceqt}$
ROE	Net income over tangible book value of equity	$\frac{ni}{ceqt}$
ROA	Earnings before interest expense over tangible book value of equity	$\frac{ni - xint + txt}{ceqt}$
PE	Market capitalization over net income	$\frac{prc \times shrout}{ni}$
Size	Log Assets	$ln\,(at)$
Book leverage	Debt (current + long-term) over assets	$\frac{dltt + dlc}{at}$
Market leverage	Debt (current + long-term) over debt + market capitalization	$\frac{dltt + dlc}{dltt + dlc + prc \times shrout}$
Non-Interest income	Non-interest income over assets	$\frac{tnii}{at}$
Interest income	Interest income over assets	$\frac{idit}{at}$
Intangibles/Assets	Intangibles over assets	$\frac{intan}{at}$
Loans/Assets	Loans over assets	$\frac{lg}{at}$
Deposits/Assets	Deposits over assets	$\frac{dptc}{at}$
Dividends/Equity	Dividends over tangible book value of equity	$\frac{dvc}{ceqt}$
Beta	Covariance (stock, market) over variance of the market	$\frac{cov(i,m)}{var(m)}$