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Market-Based Measures of Bank Risk and Bank Aggressiveness

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Proefschrift

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Contents

Chapter 1

Introduction

This thesis deals with market-based ways to measure risk and aggressiveness at banks. It has been written during the course of my PhD studies from September 2007 to December 2010 and was thus heavily influenced by the global financial crisis, which started with the subprime crisis in the summer of 2007. At first, the subprime crisis was deemed to be a local problem of the U.S. housing market, but the financial globalization soon resulted in spillovers and contagion around the globe. While most people agree that there was no single factor that caused the crisis, there is still a lively debate about which factors did actually contribute to it. Most candidates revolve around the U.S. housing bubble, particularly in the subprime market, corporate as well as household risk taking, monetary policy with low interest rates and the search for yield, or financial market factors like product innovation, product complexity, credit ratings agencies, regulatory avoidance, the shadow banking system or simply executive compensation and bonuses (see, for example, Geithner (2008), Hellwig (2008), Brunnermeier (2009), or Taylor (2009)).

No matter what the exact factors were, the recent experience has highlighted again that relying on traditional balance sheet information to infer a bank's exposure to a crisis has its drawbacks. Earlier work by Laeven and Majnoni (2003) has shown already that banks delay provisioning for loans until cyclical downturns have already set in. Huizinga and Laeven (2009) also examine the recent crisis[1] and find that banks overstate the value of distressed assets especially during the crisis period. In addition to this bank

[1] Huizinga and Laeven (2009) use data until the end of 2008.

discretion during crisis periods, it has also been well documented that banks strategically manage the reporting of their loan loss data in general[2]. Apart from the bank discretion balance sheet information has several other drawbacks. It is mostly backward looking in nature and misses other important information (for example, information in analyst reports or a bank manager's reputation). Combined with a low frequency of publication and a rapidly changing business environment, it implies that accounting data cannot reflect new information readily. This has proven to be particularly detrimental during the crisis times of 2007 and 2008 and has inspired me to investigate market-based alternatives in the three chapters of this thesis.

Market-based measures of bank risk have the potential to remedy the drawbacks of accounting data since the prices they are build on are inherently forward-looking and available at higher frequencies. Moreover, they are not under the discretion of banks and they condense several sources of information into one measure so that they offer the market's perception of a bank's business situation. This different view of a bank's business situation may help supervisors or regulators, for instance, to inform themselves about the riskiness of a bank.

The development of the financial crisis over the last three years has strongly influenced the chapters of this thesis. At first, one of the main problems was to identify and quantify credit risk at banks since it was not obvious which banks faced a large exposure to subprime loans or structured products based on subprime loans. The first paper is thus concerned with a new method to estimate a bank's credit risk exposure that incorporates traditional as well as non-traditional sources of credit risk. Since it is market-based it may give supervisors and regulators a different opinion on a bank's credit risk exposure that is not influenced by the bank itself. Moreover, it is forward-looking and available at shorter frequencies.

The proposed method in chapter two makes use of information impounded in bank share prices by exploiting differences in their sensitivity to default risk news. In the empirical implementation I identify default risk news as changes in the spreads of a high and a low risk credit default swap (CDS) index. For this I assign high and low risks to subinvestment grade and investment grade

[2] See, for instance, Wall and Koch (2000) and Hasan and Wall (2004).

indices, respectively. The two indices can then be used to estimate share price sensitivities. From these sensitivities one can in turn derive a bank's *credit risk indicator* (CRI), which is defined as the ratio of a bank's high-risk sensitivity to its total (high-risk plus low-risk) sensitivity. Loosely speaking, the CRI thus measures the share of high risk exposures in a bank's portfolio, as perceived by the market.

I estimate CRIs for the 150 largest U.S. bank holding companies. I find that the CRIs are positively and significantly related to measures of loan riskiness, such as the share of non-performing loans or loan-loss allowances. They are also positively related to factors that are often considered to proxy high loan risk, such the interest income on loans. Moreover, banks with a higher share of real estate loans seem to have significantly higher CRIs, which is consistent with the notion that a large part of the problem loans at banks were in the form of mortgages.

Since the CRI is a measure of credit risk quality, it may be a useful predictor of bank performance in downturns. This is because in a downturn the default risk of high-risk borrowers increases by more than the default risk for low-risk borrowers. Banks with a higher CRI should thus suffer relatively more. When testing this prediction using the subprime crisis I find that the CRIs are able to forecast bank failures and share price performances, even after controlling for a variety of traditional asset quality and general risk proxies. Lastly, I also find that the BHCs' aggregate CRI has not deteriorated since the beginning of the subprime crisis. This suggests that the market was aware of their (average) exposure to high risk credit. The decline in bank share prices during the subprime crisis should hence be attributed to market updates about the default risk of high and low risk loans itself (showing in a widening CDS spread for subinvestment grade and investment grade exposures) and not to updates about the composition of the BHCs' exposures to either category.

Over the course of the financial crisis, the spillovers to other financial institutions and the real economy became more apparent. Especially after the failure of Lehman Brothers in September 2008 the attention broadened from credit risk to systemic risk in general. Since then also the public eye has paid more attention to systemically relevant banks, and too-big-to-fail or too-connected-to-fail banks. Although systemic risk is not necessarily equal to tail risk, this development inspired the second paper in which banks' exposure to a large downturn in the economy (measured by the S&P500) is measured and investigated.

In this chapter a bank's (systemic) tail risk is defined as its exposure to a large negative market shock. I measure this exposure by estimating a bank's share price sensitivity to changes in far out-of-the-money put options on the market, correcting for market movements themselves. As these options only pay out in very adverse scenarios, changes in their prices reflect changes in the perceived likelihood and severity of market crashes. Banks that show a high sensitivity to such put options are hence perceived by the market as being severely affected should such a crash materialize. As this sensitivity reflects perceived exposures to a hypothetical crash, it is truly forward-looking in nature.

Based on this methodology tail risk exposures of U.S. bank holding companies are estimated. I find that the estimated exposures are inversely related to their CAPM beta. This finding is interesting as it suggests that banks that appear to have a low exposure to the market (at least in normal economic times) actually tend to be the banks that are most exposed to crashes. Moreover, I also compare this measure to the tail risk beta[3], which is a common measure of bank tail risk. I find that both measures provide different information since they are fairly uncorrelated. A potential explanation for this lies in the backward-looking nature of the tail risk beta and its reliance on large daily share price declines.

I also use my methodology to characterize the main drivers of bank tail risk. Understanding these drivers is important for regulators as it gives them information about which activities should be encouraged and which not. The findings suggest that traditional banking activities such as, for instance, lending are associated with lower perceived tail risk. However, several non-traditional activities, namely securities held for-sale, trading assets and derivatives used for trading purposes are perceived to contribute to tail risk. Interestingly, securitization, asset sales and derivatives used for hedging are not associated with an increase in tail risk exposure. This indicates that a

[3]Note, that the tail risk betas are obtained through quantile regressions.

transfer of risk itself is not detrimental for tail risk, but that non-traditional activities that leave risk on the balance sheet are. On the liability side I find that leverage itself is not related to tail risk but that large time deposits (which are typically uninsured) are. I also find that perceived tail risk falls with size, which is indicative of bail-out expectations due to too-big-to-fail policies.

The difference between the second paper and the systemic risk measurement literature is that the methodology proposed in chapter three is applied to all listed banks in the economy while the systemic risk measurement literature typically focuses on the most important banks in a financial system as only those can make a significant contribution to systemic risk (see, for instance, Adrian and Brunnermeier (2010) and Huang et al. (2010)). The contribution to the tail risk measurement literature lies in the forward-looking nature of the proposed methodology, which does not require the actual observation of a tail event to calculate a bank's exposure to it. In addition, this tail risk measure is also able to capture prolonged downturns in the economy over several weeks whereas other existing measures typically rely on shorter declines in the stock market within a few days.

Apart from the measurement of bank risk, the behavior of banks in terms of loan supply and loan pricing is also of interest in light of the recent crisis. This is because past crises have shown that banks often react to troubled loan books with credit rationing, which may have a negative impact on the real economy. However, instead of examining the supply of credit, the third paper focuses on the pricing behavior of banks, which is a different dimension of a bank's loan policy. This is because the pricing policy may give a more timely indication of changes in a bank's loan policy. When a bank is becoming less eager to make a loan, it may not always be possible to directly reduce the loan amount, due to, for example, informal commitments or reputational concerns. However, it may be possible to react through the pricing channel.

In perfectly competitive loan markets without any frictions the pricing of a loan should represent the borrower's underlying risks and thus be mainly determined by borrower and loan characteristics. In reality, however, credit markets exhibit various frictions such as, for instance, asymmetric information, imperfect competition, and legal constraints. As a result banks have to screen and monitor borrowers and may gain bargaining or market power vis-à-vis borrowers. This market power may lead to deviations from the efficient pricing rule that is based on the borrower and loan characteristics.

The third paper studies the part of the loan pricing that is not related to borrower and loan characteristics. In particular, I regress the loan spread of a syndicated loan on borrower and loan characteristics. The residual of this pricing regression is averaged over all borrowers at the bank level and is called pricing aggressiveness. It represents the part of the loan spread that cannot be explained by borrower or loan characteristics but instead by a bank's characteristics. Factors that influence these characteristics include, for example, bank credit supply conditions, the general bank strategy, and its risk appetite. This implies that aggressiveness may differ from a bank's riskiness, which is often used as a key variable in the regulatory and supervisory process. A bank with a growing risk appetite, for instance, may decide to focus lending more on riskier borrowers. Aggressiveness, on the other hand, may change even when the risk characteristics of the loan portfolio remain the same. It thus represents a different dimension of bank behavior. Given that changes in aggressiveness may have implications for the soundness of a bank, a proper understanding of banks' aggressiveness should be in the interest of supervisors and regulators. In addition, changes in a bank's loan policy may be detected more timely in the aggressiveness measure than in a bank's loan growth, which is reported on its balance sheet.

The paper in chapter four thus investigates the pricing behavior of large, international lead arrangers in the syndicated loan market. I document that banks differ in their pricing aggressiveness over time and relative to each other. Among top 10 lead arrangers a difference of 50 basis points can be observed for most years of the sample. Similarly, the difference between the ten most and ten least aggressive lead arrangers is around 150 basis points throughout the sample. Over time, the aggressiveness of banks and their cross-sectional dispersion varies considerably. Business cycle movements do not seem to be related to the time series variation, except for the last years in the sample when the subprime crisis hit the world economy. The paper also examines the relationship between aggressiveness and balance sheet items of banks. I find that higher loan loss provisions in the last year lead to less aggressiveness in the syndicated loan market suggesting that banks react to a weaker loan book by adjusting their pricing of loans. In addition, I find that aggressiveness is related to future changes in balance sheet items. This suggests that aggressiveness can be used by supervisors or regulators as a leading indicator for changes in the loan book.

Chapter 2

The Credit Risk Indicator

2.1 Introduction

It is of great value to the financial system to have informative and comprehensive indicators of the quality of banks' assets. Such indicators allow supervisors and regulators to monitor general trends in the financial system. They also permit them to identify weak banks and to put them under increased scrutiny. For example, many of the banking failures during the crisis of 2007-2009, and their systemic ramifications, could have presumably been avoided if the high-risk nature of the investments at some banks had become apparent at an earlier stage. Easily accessible information about the quality of banks' investments is also crucial for bank shareholders and debtors. It allows them to assess the performance of bank managers and to better evaluate the risks to which banks are exposed. This, in turn, enhances efficiency at banks by exposing their managers to greater market discipline.

Unfortunately, such indicators are difficult to obtain. Banks' business is complex and wide-ranging. In particular, due to the variety of information required in judging the riskiness of their lending activities, there do not exist good measures of the quality of their loan portfolios. In order to obtain proxies of loan quality one typically relies on accounting data, such as, for example, the share of non-performing loans in a bank's portfolio, or the ratio of loan-loss allowances to total loans.[1] These proxies have a range

[1] See, among others, Berger and DeYoung (1997), Wheelock and Wilson (2000), Hubbard, Kuttner and Palia (2002), DeYoung (2003) and Kwan (2003).

of shortcomings. For one, the scope of accounting data is limited. They miss important information (such as that contained in analyst reports or in the form of informal knowledge, e.g., a bank manager's reputation). They are also mostly backward looking in nature, while ideally one would like to have a measure of a bank's future risk. The low frequency of publication of accounting data also means that these proxies cannot reflect new information readily. The reliance on accounting-based data also suffers from the problem that loan-quality data is to a large extent at the discretion of banks themselves.[2] This is especially a concern if investors or supervisors base their decisions on such data. The construction of appealing indicators of asset quality is also complicated by the fact that banks nowadays undertake a variety of activities that expose them to credit risk. Beside their traditional lending business, banks trade in credit derivatives, take part in complex securitizations or grant credit lines. Many of those activities are off-balance sheet. And even if banks report them, and do so systematically, it is difficult to condense them into a comprehensive measure.

In this paper we develop a new method for measuring a bank's credit portfolio quality. Rather than using balance sheet data, this method is based on the information impounded in banks' share prices. The general appeal in using share prices is that they represent the market's overall assessment of a bank, and thus reflect a wide range of information. Our basic idea for how information about credit quality can be extracted from share prices is the following. Suppose that there are two types of loans in the economy, high-risk and low-risk loans, and suppose a bank's portfolio contains mostly high-risk loans. That bank's share price should then react relatively strongly to news about changes in the default risk of high-risk loans, but less so to news about low-risk loans. Thus, the bank's relative share price sensitivity to either type of news gives information about the perceived quality of its loan portfolio.

In our empirical implementation we identify default risk news as changes

[2]There is widespread evidence that banks strategically manage the reporting of their loan loss data (see Wall and Koch (2000) for a survey of U.S. evidence and Hasan and Wall (2004) for international evidence). There is also evidence that banks delay provisioning for loans until cyclical downturns have already set in (Laeven and Majnoni (2003)) and that they overstate the value of distressed assets (Huizinga and Laeven (2009)).

in the spreads of a high and a low risk credit default swap (CDS) index. For this we assign high and low risks to subinvestment grade and investment grade indices, respectively. The two indices can then be used to estimate share price sensitivities. From these sensitivities one can in turn derive a bank's *credit risk indicator* (CRI), which is defined as the ratio of a bank's high-risk sensitivity to its total (high-risk plus low-risk) sensitivity. Loosely speaking, the CRI thus measures the share of high risk exposures in a bank's portfolio, as perceived by the market. It thus presents a simple market-based alternative to the risk-weights currently used to compute regulatory capital requirements, which either rely on crude risk categories (standardized approach of Basel I) or assessments generated by the bank itself (advanced approach of Basel II).[3]

We believe that this measure has several attractive features. Since it is market-based, it is forward looking and can incorporate new information quickly. It is also a comprehensive measure of a bank's credit quality. For example, for a bank's CRI it does not matter whether the bank acquired a high-risk exposure via lending to a low quality borrower, or by writing protection on a low quality underlying in the CDS market, or by buying a junior tranche of a Collateralized Loan Obligation. Another advantage of the CRI is that it is based on the market's assessment of the bank, and not on the bank's assessment of itself. It is thus more difficult to manipulate.

We estimate CRIs for the 150 largest U.S. bank holding companies (BHCs).[4] We find that their CRIs display substantial variation. Among the ten largest surviving BHCs, for example, Citigroup has the largest CRI, implying that it is considered as having relatively worse exposures. Interestingly, Citigroup is up to now also the bank that has incurred the largest write-downs in the subprime crisis. We also analyze the evolution of the BHCs' aggregate CRI over time which allows us to track perceived credit quality at the BHCs. We find that during our sample period (February 2006 until March 2010) the aggregate CRI was surprisingly stable. In particular, it did not increase between February 2007 (when problems with subprime loans first materialized in the financial system) and the height of the subprime crisis. This

[3] We thank an anonymous referee for suggesting this use of the CRI.

[4] The full list of CRIs can be found at http://lyrawww.uvt.nl/~wagner/cri.xls.

suggests that the market was aware of the BHCs' overall high-risk exposures prior to the crisis. The decline in bank share prices during the subprime crisis should hence be attributed to market updates about the default risk of high and low risk loans itself (showing in a widening CDS spread for subinvestment grade and investment grade exposures) and not to updates about the composition of the BHCs' exposures to either category. This is an interesting finding as it indicates that there was not a general market failure in anticipating risks in the financial system but rather that the market did well in recognizing risks in one dimension (bank exposures to high risk credits) but not in another (a general worsening of default risks in the economy).

We next address the question of how a bank's CRI is related to traditional measures of asset quality. We find that the CRIs are positively and very significantly related to measures of loan riskiness, such as the share of non-performing loans or loan-loss allowances. They are also positively related to factors that are often considered to proxy high loan risk, such the interest income on loans. We also find that banks with a higher share of real estate loans have significantly higher CRIs, which is consistent with the notion that a large part of the problem loans at banks were in the form of mortgages.

As a measure of credit risk quality, the CRI may be a useful predictor of bank performance in downturns. This is because in a downturn the default risk of high-risk borrowers increases by more than the default risk for low-risk borrowers. Banks with a higher CRI should thus suffer relatively more. We test this prediction using the subprime crisis. For this we first use the CRI to dynamically predict bank failures during the subprime crisis. We find that the CRI is able to predict failures at a one and a two quarter horizon. This predictive power survives when we control for a variety of other variables, such as various proxies of loan quality, bank leverage, share price beta and distance-to-default. Next we study whether the CRI can also predict share price performance of banks during the subprime crisis. For this we regress a bank's share price change in the year following June 2007 (the time when problems with subprime loans became a widespread phenomenon) on its CRI estimated using information before this date. We find a significant and negative relationship between the bank's CRI and its share price performance. The relationship again survives both in significance and magnitude if we include the other controls. For both forecasting exercises we also find that traditional measures of asset quality do not explain very well banks' performance during the subprime crisis.

The remainder of this paper is organized as follows. The next section reviews the related literature. In Section 2.3 we explain our methodology for estimating the CRI. The section also contains a general discussion of the CRI. Section 2.4 contains the empirical analysis. The final section concludes and briefly discusses uses for the CRI.

2.2 Related Literature

In recent years there has been a growing interest in using market-based information to measure bank risk (for surveys, see Flannery (1998) and Flannery (2001)). This is on the back of evidence suggesting that the market does well in evaluating the risks at financial institutions. The existing literature suggests that investors are able to distinguish between banks based on their exposures to certain types of risks or asset compositions. This is true for share prices (see, for instance, Flannery and James (1984a), Sachs and Huizinga (1987) and Smirlock and Kaufold (1987)) as well as for bond and subordinated debt spreads (see, for example, Flannery and Sorescu (1996), Morgan and Stiroh (2000), and Hancock and Kwast (2001)). There is also evidence that market information has predictive power for banks, being it forecasting of bank performance (Berger, Davies and Flannery (2000)), rating changes (Evanoff and Wall (2001), Krainer and Lopez (2004), and Gropp, Vesala and Vulpes (2006)) or default (Gropp, Vesala and Vulpes (2006)).

Spurred by the crisis of 2007-2009, there has recently been a focus on developing market-based measures of system-wide risk. In an earlier contribution, Elsinger, Lehar and Summer (2006) develop a framework for systemic risk assessment using market data to separate systemic risk into contagion risk and correlated exposures. Acharya et. al. (2009) propose the Marginal Expected Shortfall (MES) as a systemic risk measure. This measure is defined as the loss by an institution when the market is in its left tail and is estimated from share price data. Huang, Zhou and Zhu (2009) construct a measure of systemic risk in the financial system based on probabilities of default and correlations that are estimated from asset prices.

While our approach also captures system-risk (in that we measure exposures to economy-wide credit risk), it differs from these measures in that it focuses on the asset side of banks (to our best knowledge, the CRI is the first market-based measure that quantifies asset risk at banks). The CRI also differs conceptually from these, and other market-based measures. Market-based measures of bank risk, such as the distance-to-default or CDS spreads, typically tell us the perceived proximity of a bank (or a set of banks) to default at a given point in time. By contrast, the CRI measures the *exposure* of a bank to an economic downturn (in which high risk assets perform worse than low risk assets). It is hence particularly useful for identifying in advance banks that are vulnerable to downturns in the economy. For example, in the years prior to the crisis of 2007-2009, the risk of a downturn was perceived as low. Market-based measures of bank defaults (such as CDS spreads or the distance-to-default) consequently indicated a low probability of default at the time. However, banks had already accumulated high risks at this point (and our empirical results suggest that the market was aware of this) and hence were perceived as vulnerable in terms of their CRI.

In our empirical implementation we use changes in indices of CDS spreads to identify variations in economy-wide credit risk. CDS spreads have the advantage that they are a relatively clean and efficient measure of default risk. For example, there is evidence that a substantial part of price discovery takes place in these instruments (see Blanco, Brennan and Marsh (2005) and Norden and Weber (2009)). There is also evidence that lending-relevant credit risk information is first revealed in CDS markets, before it is incorporated in other markets (Acharya and Johnson, 2007) or in ratings (Norden, 2009). CDS markets also did not seem to lose their informational role during the subprime crisis (which is important for our analysis as our sample covers the crisis period). For example, Eichengreen et. al. (2009) show that CDS prices can be used to understand how risks are spreading among banks during the crisis. King (2009) provides evidence that the value of government rescue packages is reflected in CDS spreads.

In part of our analysis we relate estimated share price sensitivities to bank balance sheet variables. Such an approach has also been followed in the literature that studies the interest rate sensitivity of bank share prices. The typical procedure in this literature is to estimate in a first step share price sensitivities to interest rate changes, and in a second step to relate these sensitivities to balance sheet information. For example, Flannery and James (1984a) show that interest rate sensitivities are related to proxies of maturity mismatch at banks, while Flannery and James (1984b) show that sensitivities depend on the composition of banks' balance sheets. Hirtle (1997) finds that they are also related to derivative usage at banks. Our paper follows a similar methodology and finds that default risk sensitivities of bank share prices are as well related to balance sheet characteristics.

The forecasting exercises in the second part of the paper also relate our work to a strand of the asset pricing literature that has used credit indices to forecast aggregate stock returns (e.g., Fama and French (1989), Fama (1990), Schwert (1990)). The approach in our paper differs in that we do not use credit spreads themselves for forecasting. Rather, we estimate share price sensitivities to credit spreads and use these sensitivities as a proxy for how banks will fare in a downturn. This approach also sets us apart from another important strand of the asset pricing literature which estimates factor loadings and studies whether assets with different factor loadings have different *required* returns (e.g., Cremers (2002)).

2.3 The Credit Risk Indicator

Consider a prototypical balance sheet of a bank. On the asset side we have securities (S) and loans ($Loans$). On the liability side we have debt (D) and equity (E), with equity being the residual claim ($E = S + Loans - D$). In terms of market values ($V(.)$), we can thus write

$$V(E) = V(S) + V(Loans) - V(D). \tag{2.1}$$

We express all variables in unit of shares. $V(E)$ is simply given by the bank's share price. $V(D)$ can be approximated by its book value (discounted at an appropriate interest rate). For the loans, we have to take into account the risk of default. The expected loss on a loan EL is given by $EL = PD \cdot LGD$, where PD is the probability of default and LGD is the loss given default (expressed as a share of the face value). We assume that there are two types of loans, high risk and low risk loans. The amounts due on each type of loan are denoted with H and L, respectively, and we have $EL^H > EL^L$. The value of the loan portfolio can then be expressed as

$$V(Loans) = H(1 - EL^H) + L(1 - EL^L). \tag{2.2}$$

We define the *Credit Risk Indicator* (CRI) as the share of high risk loans in the loan portfolio

$$CRI = \frac{H}{H + L}. \tag{2.3}$$

We use as a proxy for the expected losses on high and low risk loans the spreads of two (economy-wide) Credit Default Swaps (CDS) indices (these indices are discussed in greater detail in Section 2.4.1). CDS spreads provide a fairly clean measure of default risk since they represent the compensation the market requires for taking on credit risk. This is because the writer of the CDS has to be compensated by the buyer of protection for the expected loss on the underlying credit (consisting of the product of PD and LGD). The price of a CDS (which is expressed as a spread) hence approximates the expected loss. We can thus write for the CDS prices of high and low risk exposures

$$CDS^H = EL^H \text{ and } CDS^L = EL^L. \tag{2.4}$$

In our empirical work, CDS^H and CDS^L will be the prices (spreads) of a CDS-index consisting of a representative sample of subinvestment grade and investment grade exposures in the economy.

The CRI can be obtained as follows. We can first write equation (2.1) in terms of changes

$$\triangle V(E) = \triangle V(S) + \triangle V(Loans), \tag{2.5}$$

where $\triangle$ indicates the (absolute) change from $t - 1$ to t and where we have assumed constant debt.[5] We can replace $V(Loans)$ in (2.5) with the expression derived earlier and approximate the change in the value of a bank's

[5] Since debt changes occur only infrequently, assuming constant debt is a reasonable approximation for regressions that are on a daily frequency. In addition, a bank's debt changes cannot be contemporaneously correlated with (aggregate) CDS spread changes (as there is a signficiant decision and implementation lag associated with debt changes) and hence their omission should not bias the CDS estimates.

security portfolio with the change in a market index, denoted M. Given security holdings of S, the absolute change is then given by $\triangle V(S) \approx \triangle M \frac{S}{M}$. We hence have for the change in the bank's share price:[6]

$$\triangle p = \frac{S}{M} \triangle M - H \triangle CDS^H - L \triangle CDS^L. \tag{2.6}$$

We can then estimate the following relationship at the bank level

$$\triangle p_{i,t} = \alpha_i + \beta_i \triangle M_t + \gamma_i \triangle CDS_t^H + \delta_i \triangle CDS_t^L + \phi_i \triangle \mathbf{Z}_t + \varepsilon_{i,t}, \tag{2.7}$$

where i denotes the bank, t denotes time, and $\mathbf{Z}$ is a vector of control variables. Noting that $\gamma_i = -H_i$ and $\delta_i = -L_i$, the CRI ($= \frac{H_i}{H_i+L_i}$) can be expressed as

$$CRI_i = \frac{\gamma_i}{\gamma_i + \delta_i}. \tag{2.8}$$

We can hence obtain the CRI by first estimating $\widehat{\gamma}_i$ and $\widehat{\delta}_i$, and then applying (2.8).

2.3.1 Discussion of the Properties of the CRI

In deriving the CRI we have presumed that a bank's credit risk derives exclusively from loans. Banks, however, also have credit risk exposures from other investments. Since the CRI is derived from share price sensitivities to credit risk in general (and not specifically loan-risk), it captures those as well. The CRI should hence be interpreted as a measure of the overall riskiness of a bank's credit exposures. For example, a bank may have a large CRI because it has sold credit protection on a risky borrower using CDS or because it has a risky bond portfolio (consisting of, for instance, mainly subinvestment grade names). Credit exposures may also arise from banks' securitization activities. For example, in a Collateralized Loan Obligation (CLO) banks typically sell the lower-risk senior and mezzanine tranches, but retain the high risk equity tranche (these tranches are typically unrated but perceived

[6] Note that the equivalent of (2.6) with relative changes does not hold. Dividing (2.6) by p we obtain (focusing on high risk loans only): $\frac{\triangle p}{p} = -H \frac{CDS^H}{p} \frac{\triangle CDS^H}{CDS^H}$. Hence, for a given loan portfolio H relative changes in the CDS spread ($\frac{\triangle CDS^H}{CDS^H}$) would only translate into relative share price changes ($\frac{\triangle p}{p}$) when $\frac{CDS^H}{p}$ is constant over time.

to be well below investment grade). This lowers the average quality of the bank's credit exposures and increases a bank's CRI. By contrast, if a bank were to acquire AAA-rated (super-senior) tranches from securitizations, its average credit risk exposure may improve and hence its CRI would decrease. The CRI will also reflect the effect of risk mitigation techniques, such as through collateralization of loans. If, for instance, a bank has a large number of high risk loans, but at the same time these loans are fully collateralized, its share price should not be sensitive to news about high risk loans. The bank's estimated CRI will then be low and hence reflect that its high risk exposure is effectively small.

In our empirical implementation of equation (2.6) we will include a market index that has been orthogonalized with the CDS indices. The consequence of this is that our estimated sensitivities do not only capture the direct effect of changes in the CDS indices on bank equity, but also an indirect effect because variations in default risk may influence bank equity through changes in the market return.[7] In the same way as, say, the high risk CDS index proxies for changes in the value of high-risk *credit exposures* of banks, changes in the market index triggered by changes in the high risk CDS index proxy for high-risk *equity exposures* of banks (more precisely: for equity exposures to firms with high default risk). The estimated CRI will hence reflect the overall share of high risk exposures at banks, coming both from debt and equity holdings. This is important for using the CRI as an indicator for how banks will perform in a downturn. In a downturn, both equity and debt of high (default) risk firms will suffer relatively more than for low risk firms. Banks that have a large exposure to high-risk firms are thus expected to perform worse, regardless of whether the exposure comes through debt or equity. By not including the indirect effect, the CRI would thus miss a part of the exposure. This issue is probably less important for our study since U.S. banks have low equity holdings of firms, but might be crucial when estimating CRIs on international banks.

We have assumed that banks have either high or low-risk exposures, which in our empirical implementation we take to be representative subinvestment

[7] This point has been shown formally by Giliberto (1985) in the context of share price sensitivities to interest rates (rather than CDS spreads).

and investment grade exposures (as given by the two respective CDS indices). Banks have, however, a variety of credit exposures, which will obviously not all fall neatly into these two categories. The CRI is thus not strictly the share of a bank's subinvestment grade exposures, but should be more generally interpreted as a measure of the average riskiness of a bank's credit exposures. Suppose, for example, that a bank has a loan portfolio that consists only of loans that have risk characteristics just between the representative investment and subinvestment grade loan. The banks' share price should then (on average) react similarly to subinvestment and investment grade CDS spread changes. Hence the bank's CRI would be $\frac{1}{2}$ (which is the same as for a bank whose loan portfolio consists of equal parts of subinvestment and investment grade exposures) even though the bank has no real subinvestment exposures at all. Moreover, since the representative investment and subinvestment grade exposures in the CDS index are not representing the lowest and highest possible credit risk in the economy, a bank's CRI is also not constrained to lie between zero and one. For instance, a bank that mainly has exposures of a higher quality than the representative investment grade credit in the CDS index will have a CRI smaller than zero, while banks with a portfolio quality below the representative subinvestment grade will have a CRI greater than one.

While ideally we would like to measure share price sensitivities to a basket of exposures consisting of all credit types (i.e., commercial, real estate, consumer, ...), CDS indices for such baskets do not (yet) exist. By contrast, CDS indices are readily available for corporate exposures, for which there also exist high and low risk baskets. In our empirical implementation we will thus measure sensitivities to corporate credit spreads. Credit spreads, however, will be correlated across exposures (for example, in an economic downturn default risks typically increase for all loan types). Hence our estimated CRI will also (at least partially) capture other credit types. In addition, high risk exposures are likely to be correlated within the bank: a bank that follows an aggressive strategy is expected to simultaneously extend high risk corporate and high risk real estate loans (this is confirmed by our empirical finding that the CRI is positively related to real estate exposures at banks). Nevertheless, if broader CDS indices become available they should be used to improve estimation of the CRI.

It should be emphasized that the CRI measures the *relative* sensitivities to high and low credit risk, that is, it relates to the *composition* of the bank's credit exposure. It should hence not be confused with a bank's absolute sensitivity to credit risk. The latter will be determined, besides the composition of the credit portfolio itself, also by the size of its credit portfolio and its leverage. For example, all else being equal, the share price of a highly leveraged bank will be more sensitive to changes in credit conditions than is the case for a bank with lower leverage.[8]

Since the CRI is derived from share prices, it represents the market's assessment of banks' credit risk. This assessment will be based on a variety of information, including for instance accounting data and analyst forecasts. However, as the subprime crisis has reminded us, banks are opaque institutions.[9] Hence, it should be kept in mind that the CRI is the equivalent of the market's "best guess" of a bank's portfolio credit quality, and may hence differ from its true quality.[10] Moreover, even though share prices may contain a wide range of useful information, they may arguably also be subject to noise. An advantage of our empirical implementation is that it computes CRIs from daily share price responses over a longer period of time (1025 trading days in our sample). The impact of any noise in returns is likely to cancel out over so many observations and thus its influence on the CRI is likely to be limited. Another advantage is that the CRI relies on sensitivities, and not on share price levels. If there is, for example, a bubble due to (unjustified) optimism about credit risk, this will affect the bank's valuation, but not its

[8] Note also that a high CRI is not necessarily a sign of bad management if the bank is adequately compensated for the risk. Nevertheless, a high CRI bank is of concern to regulators since this bank would be more vulnerable to downturns (the bank should equally also profit from a boom but this is of less interest to regulators as they mainly care about downside risk).

[9] Whether banks are more opaque than other institutions remains a debated issue. Morgan (2002) finds that there are more rating disagreements for banks, suggesting higher opacity. Flannery, Kwan and Nimalendran (2004), by contrast, analyze market microstructure properties (such as bid-ask spreads) and find no evidence that banks are less transparent than similar non-financial firms.

[10] An observed change in a bank's CRI thus does not necessarily imply that the bank has actually altered its credit portfolio, but may also be due to new information that causes the market to re-evaluate the credit quality of a bank. We return to this point later in Section 2.4.2 when we consider the evolution of banks' CRIs.

responsiveness to credit risk. It should also be kept in mind that we measure *relative* share price sensitivities. Thus, even if there is some mispricing which affects the absolute response to credit risk news, it is difficult to conceive how such a mispricing might alter the relative response to high and low risk credit news.

The fact that the CRI measures relative sensitivities also means that our analysis is not affected if the value of bank equity does not change one-to-one with changes in the value of the bank's loan portfolio. While equation (2.1) implies that $\frac{\partial V(E)}{\partial V(Loans)} = 1$, this will for instance not be the case under the Merton-model due to the option value of equity. Sensitivities will then, for example, also be influenced by the bank's asset risk. In Appendix A we show that this does not affect the estimated CRI. The reason is that if $\frac{\partial V(E)}{\partial V(Loans)} \neq 1$ (and possibly also bank dependent) each CDS sensitivity will be scaled by the same factor $(\frac{\partial V(E)}{\partial V(Loans)})$. Hence this effect cancels out when we compute relative sensitivities, and the estimated CRI will still measure the true share of high risk loans.

Another issue is that CDS spreads may not only reflect credit risk. This is even though CDS prices are typically considered to be a relatively clean measure of credit risk (as opposed to bond spreads, for example). In fact, recent research has suggested the existence of other pricing factors in CDS spreads, such as liquidity and risk premia (see, e.g., Amato (2005) and Bongaerts, de Jong and Driessen (2009)). If CDS prices move because of news unrelated to credit risk, this may result in the absolute share prices responsiveness to credit risk being underestimated. However, this is less of a concern in our case since this will be the case for both high and low credit risk and hence the CRI is not necessarily affected.

2.4 The Empirical Evidence

2.4.1 Data

We estimate CRIs for U.S. bank holding companies (BHCs) that are classified as commercial banks and listed in the U.S.. We exclude foreign banks (even when listed in the U.S.), pure investment banks and banks for which complete data was not available. Of the remaining banks, we take the 150 largest ones by asset size.

We collect daily data on bank share prices, two CDS indices (to be discussed in more detail below), short-term and long-term interest rates, and a market return from Datastream and the FRED database. Additionally, various balance sheet data are collected from the FR Y-9C Consolidated Financial Statements for BHCs. The sample ranges from February 01, 2006 to March 05, 2010. The starting point of the sample was determined by the availability of reliable CDS data.

For the high and low risk CDS index we take the "Dow Jones CDX North America Crossover" index ("XO index") and the "Dow Jones CDX North America Investment Grade" index ("IG index"). These indices are jointly managed by the Dow Jones Company, Markit and a consortium of market makers in the CDS market and are considered the leading CDS indices for North American underlyings. The IG index consists of 125 equally weighted U.S. reference entities with ratings ranging from BBB up to AAA. These reference entities are the most liquid entities traded in the CDS market and represent large companies in various industries. The XO index consists of 35 equally weighted U.S. reference entities that have ratings ranging from B up to BBB (hence the term crossover, as it also represents credit risk on the border to investment grade quality). The reason why this index has fewer reference entities is not known to us but is likely to be due to the fact that there are less (liquid) CDS of such underlyings.

Taken together, both indices cover a large part of the overall rating distribution (from AAA to B). We checked the distribution of loans by U.S. banks since 2000 using the Dealscan database (which contains syndicated loans) and found that the share of rated loans outside this range only 2%. Thus the two indices seem to capture a large part of the relevant risk profiles. It should be noted that the indices also contain financial institutions, which is desirable for our purpose since banks may also grant loans to other banks.[11]

Both CDS indices are expressed in basis points (bps) of spreads. A higher

[11] An alternative to using CDX indices is the ABX index (which covers subprime mortgage loans). However, our aim in this paper is to estimate a general credit risk indicator, and not one that is tailored to the crisis of 2007-2009.

spread implies a higher cost of hedging credit risk, and hence a higher implied default risk. The XO-index thus should have a larger spread as it represents riskier underlyings: during our sample period its average spread was around 280 bps, compared to around 120 bps for the IG index. In addition, as typical in crises, the spread widens during the subprime crisis (from around 100 bps in the beginning of 2007 to up to 400 bps at the height of the crisis).

The indices are available for different maturities, ranging from one to ten years. We focus on the 5-year maturity index, which is the reference maturity for CDS contracts. The indices are rolled over twice a year (that is, the constituent's list is checked and adjusted if necessary) and assigned a new roll number. We always use the newest roll ("on-the-run"), as this is the most liquid one. When changing between different rolls, the underlying reference entities may change as well (typically, between 6-9 entities are replaced from one roll to another). This may cause a jump in the index unrelated to a change in credit risk in the economy. The average CDS price change (in absolute terms) on rollover days is 9 bps for the IG-index and 28 bps for the XO-index. These changes seem large and we hence include dummy variables for the rollover dates in our econometric analysis (however, our results are essentially invariant to their exclusion).

For our main regression (equation 2.7) we use the following variables. For the control variables $\mathbf{Z}_t$ (which capture proxies for discount rates that might affect $V(D)$ and possibly $V(Loans)$) we include a short term and a long term interest rate (the 1-month and the 10-year Treasury Constant Maturity Rate) and an inflation-proxy (the difference between the 10-Year Treasury Constant Maturity Rate and the 10-Year Treasury Inflation-Indexed Security at Constant Maturity). For the market return, we take the S&P 500. We orthogonalize the S&P 500 return with both CDS indices in order to include only the part of the market movements that are unrelated to changes in credit risk. As discussed earlier, this has the effect of attributing any indirect effect of CDS spreads on bank values (through changes in the market index) to the CDS sensitivities.

The CDS-indices themselves will also be correlated. This may result in their individual regression coefficients being not reliably estimated. We hence orthogonalize the CDS prices on each other. This effectively attributes the common component of credit risk changes to either the high or the low credit risk, depending on the chosen direction of the orthogonalization. A direct consequence of this will be that the importance of the risk type (high or low) to which the common factor is allocated will be overestimated. However, this not a problem for our analysis since we are mainly interested in how CRIs differ across banks. This ranking should not be influenced by the orthogonalization method since the bias it may introduce affects the CRIs of all banks. We have verified this by computing the CRIs under either method of orthogonalization: their correlation across banks is near one ($\rho = 0.95$) and the rank-correlation is equal to one. For the regressions reported in the paper, we decided to orthogonalize the IG-spread (thus, we include only IG-spread changes unrelated to changes in the XO-index).

2.4.2 The Aggregate CRI

Before turning to the estimation of the bank-specific CRIs, we first analyze their aggregate CRI. For this we run a pooled version of equation (2.7). Specifically, we estimate the following regression on daily data:

$$\Delta p_{i,t} = \alpha + \beta \Delta S\&P500_t^{(orth)} + \gamma \Delta CDS_t^{XO} + \delta \Delta CDS_t^{IG(orth)} + \phi \Delta \mathbf{Z}_t + \varepsilon_{i,t}, \tag{2.9}$$

where $p_{i,t}$ is a bank's share price, $S\&P500_t^{(orth)}$ the orthogonalized S&P 500 index, CDS_t^{XO} the XO CDS index, $CDS_t^{IG(orth)}$ the orthogonalized IG CDS index, and $\mathbf{Z}_t$ the vector of control variables. In addition we also include dummies for each day on which either the IG or the XO-index is rolled over. We exclude day-bank observations at which a stock was not traded in order to reduce the impact of illiquidity in bank stock prices. Note that all variables are expressed in absolute changes, consistent with the derivations in Section 2.3. This implies that banks with higher (average) share prices will also tend to have larger changes. In order to avoid issues arising from this, we normalize each bank's share price by its mean (the results, however, are essentially invariant to this normalization).

Table 1, column 1, contains the regression results. All variables have the expected sign and are significant. In particular, the two variables of interest, ΔCDS^{XO} and $\Delta CDS^{IG(orth)}$, are highly significant and have the correct, that is negative, sign. The second but last row in the table reports the implied CRI, as computed from equation (2.8), which is 0.1557. As discussed earlier, the absolute level of a CRI on its own is not informative since it is influenced by the orthogonalization method. However, we note that the CRI is quite precisely estimated: the last row in the table shows that the 95% confidence interval for the CRI (computed using the (non-linear) Wald-Test) is between 0.1510 and 0.1603.

It is, however, informative to study whether the aggregate CRI has changed over time. For this we split our sample into three equal parts and estimate separate CRIs for each subsample (cutoff dates are June 08, 2007 and October 20, 2008). The results are reported in the last three columns of Table 1. One can see that the sensitivities in each subsample are still precisely estimated. The implied CRIs are similar but seem to exhibit a downward trend (0.1879, 0.1637 and 0.1289).

We next look at the evolution of the CRI in more detail. For this we use rolling window and recursive window analysis. Figure 1 shows the coefficients of the aggregate CRIs of the rolling and recursive windows over the entire sample period. The rolling window uses a window-length of 240 trading days (roughly equal to one calendar year), which is the same as the initial length of the recursive window. For both methods the coefficients are plotted against the last day of the windows. Looking at the rolling window first, one can see that the aggregate CRI is relatively stable over time, except for three periods: February 2007, July/October 2007 and September 2008/February 2009. During these periods the CRI fluctuates widely but stabilizes itself afterwards close to (or a bit below) its previous level.

One may suspect that these periods of instability are due to noise inherent in daily data. We have thus re-estimated the CRI using weekly data. However, the rolling windows were virtually unchanged and the precision of the CRI estimates even declined (the confidence intervals widened). The reason for these fluctuations in the CRI rather lies in the fact that these periods are associated with major turbulences in financial markets. The first period (February 2007) coincides with the time at which first warning signs about large losses connected to subprime lending emerge (on February 22 HSBC fires the head of its US mortgage lending business as losses reach $10.5bn;

the largest US house builder DR Horton warns of huge losses from subprime fall-out (March 8), and shares in New Century Financial, one of the largest subprime lenders in the US, are suspended on March 12 due to fears that it might be heading for bankruptcy). The second period (Summer/Fall 2007) is typically considered as the time where subprime problems become apparent on a wider scale. It starts with Bear Stearns bailing out two of its funds exposed to the subprime market for $3.2bn (June 22). Various European and American banks also revealed further large losses connected to subprime mortgages. In addition, global stock markets fall dramatically and interbank money markets dry up. The third period (September 2008/February 2009), where the CRI fluctuates more moderately, coincides with failure of Lehman brothers and the subsequent financial turmoil.

One may conjecture that the estimation of the CRI was obscured during these periods because they were considered by large and erratic swings in both bank stock prices and CDS prices. This is confirmed by the standard errors of the estimated of CRIs for the first two periods: while the median standard error of a CRI in a rolling window is about 0.005, the standard error reaches 0.05 in the first trouble period and 0.07 in the second. The CRIs in these periods are hence not precisely estimated. This suggests that regulators should only take seriously changes in CRIs when this does not go along with a loss of precision.

The third period, however, is different. The standard errors are only slightly elevated in this period. In addition, the CRI seems to decline during this period, which is somewhat unexpected. The reason for this is, however, of purely mechanical nature: this is the point where data with high estimated CRIs (summer 2007) falls out of the window. This is confirmed by looking at the recursive window, which does not show a substantial decline in the CRI over this period but rather suggests that the CRI was constant. The observation that the CRI did not increase during the Lehman failure is easily explained by the fact that the Lehman failure itself was not driven by worsening credit portfolios but rather by liquidity and counterparty issues.

The recursive window also shows a slight (but persistent downward) trend in the CRI since March 2008. This is consistent with the fact that after 2007 most banks clean up their loan portfolio by writing off bad loans. Since the majority of these loans were high risk in nature, this implies that their portfolio composition (that is, the CRI) shifted to better quality. Note also that the CRI has been rather stable since mid 2009, the time when conditions in the financial system started to stabilize. Going forward we would expect the downward trend in the CRI to continue as banks further write-down bad loans and are probably less inclined to extend new high-risk loans. However, once banks have repaired their balance sheets they may want to again increase their risk-taking and hence their CRIs may increase.

Looking at the overall evolution of the CRI as represented by the recursive window, a striking observation is that the CRI did not jump to (permanently) higher levels since the beginning of the sample period. This suggests that the market was (on average) aware of the BHCs' exposures to high risk investments well before the subprime crisis (otherwise we should have seen a significant increase in the CRI). This finding is interesting given that bank share prices declined significantly during the subprime crisis, which shows that not everything has been anticipated. In our context, there are two reasons why share prices can fall systematically. The first is an update about the proportion of high to low risk loans while the second is an update about the default risk associated with each of the loan categories. The fact that the CRI did not deteriorate since the start of the crisis suggests that the update was on the latter and not the former dimension.[12] This is also consistent with the fact that the CDS spreads of high and low risk borrowers increased substantially during the crisis. Thus, the market seems to have been aware of the exposures of banks but did expect a downturn that increases default risks on either loan type.

2.4.3 Individual CRIs

We now turn to the analysis of the BHCs' individual CRIs. For this, we estimate equation (2.9) on the bank level. That is, we estimate for each

[12] Obviously, there have been updates about individual bank's exposures. Our results only say that there is no net effect for the average bank.

bank the following equation

$$\Delta p_{i,t} = \alpha_i + \beta_i \Delta S\&P500_t^{(orth)} + \gamma_i \Delta CDS_t^{XO} + \delta_i \Delta CDS_t^{IG(orth)} + \phi_i \Delta Z_t + \varepsilon_{i,t}. \quad (2.10)$$

The significance of the credit exposure estimates is generally high. For all except three banks the joint credit exposure $\gamma_i + \delta_i$ is significant at the 5% level (we look at joint exposure since insignificance of either exposure may simply mean that the bank has little exposure to this type). In most cases significance is also very high; the average t-statistics exceed 10 (in absolute values).

Using equation (2.8), we can then compute for each bank its CRI from the estimated γ_i and δ_i. Table 2 reports some summary statistics. The mean CRI across all 150 banks is 0.1670, which is similar to the previously estimated aggregate CRI, 0.1557. The (cross-sectional) standard deviation of the CRIs is 0.0561. The lowest CRI among the banks is 0.0546, while the largest CRI takes the value of 0.4132.

Figure 2 depicts the individual CRIs, where banks have been ordered by asset size. Most banks have a CRI in the range from 0.1 and 0.2. There are outliers but only relatively few (it turns out that among the seven banks with a CRI of above 0.3, two actually failed). From the ten largest surviving BHCs, Citigroup (the last dot) has the highest CRI. Interestingly, Citigroup is up to now also the bank with the largest accumulated write-downs during the subprime crisis. Besides, no obvious pattern can be detected from the figure. It is, however, reassuring that there is substantial cross-sectional variation in the CRIs, suggesting that the market differentiates across banks in terms of credit risk sensitivities.

2.4.4 The CRI and Other Measures of Bank Risk

In this section we study whether (and how) a bank's CRI is related to traditional measures of loan quality, and proxies of bank risk more generally. In the first place this will first inform us about whether the CRI really captures credit risk. It may also help us to understand whether the CRI contains information about general lending risk, or applies only to specific segments of lending. In addition, we will also relate the CRI to some basic bank characteristics; this may inform us about how the CRI depends on the business model of banks.

The simplest way to study how the CRI is related to other bank variables is to look at the correlation between the estimated CRI and these variables. However, this is not an efficient procedure since information from the first step (the estimation of the CRIs itself) is then not fully used in the second step (computation of the correlations). In particular, the precision with which the CRIs are estimated differs across banks and one would like to give banks with less precisely estimated CRIs a lower weight in the second step. In addition, the two step procedure also causes the problem of generated regressors (see, for example, Pagan, 1984).

We instead develop a method which allows us to (efficiently) estimate the relationship in one step.[13] For this we adjust the equation for the aggregate CRI (2.9) in order to allow the CDS-sensitivities to depend on a bank characteristic, say variable X. More specifically, we include in the regression for each CDS-spread an interaction term with X, where X is expressed relative to its sample mean ($\widetilde{X}$). We thus estimate the following regression:

$$\begin{aligned} \Delta p_{i,t} &= \alpha + \beta \Delta S\&P500_t^{(orth)} + (\gamma + \eta(X_i - \widetilde{X}))\Delta CDS_t^{XO} \\ &\quad +(\delta + \theta(X_i - \widetilde{X}))\Delta CDS_t^{IG(orth)} + \phi \Delta Z_t + \varepsilon_{i,t}. \end{aligned} \qquad (2.11)$$

Note that if the coefficients for the interaction terms are zero ($\eta = \theta = 0$), this equation is identical to equation (2.9). The CRI is, as before, given by the ratio of the estimated high-risk CDS-sensitivity and the total CDS sensitivity. Analogous to equation (2.8), this is

$$CRI(X) = \frac{\gamma + \eta(X - \widetilde{X})}{\gamma + \eta(X - \widetilde{X}) + \delta + \theta(X - \widetilde{X})}. \qquad (2.12)$$

Differentiating equation (2.12) with respect to X and evaluating at the mean ($X = \widetilde{X}$) yields

$$CRI\,'(X)_{X=\widetilde{X}} = \frac{\eta\delta - \theta\gamma}{(\delta + \gamma)^2}. \qquad (2.13)$$

[13]Note that our setup differs from the usual two-step regression problem in that the variable of interest that is estimated in the first step (the CRI) is a (non-linear) combination of coefficients, and not simply a coefficient itself.

$CRI\,'(X)_{X=\widetilde{X}}$ is the counterpart of the coefficient on X in a two-step regression where in the second step the CRIs (estimated in the first step) are regressed on X. The relationship between the CRI and a variable X can thus be estimated as follows. We first estimate (2.11). From the coefficients we then calculate the coefficient for X, $CRI\,'(X)_{X=\widetilde{X}}$, using equation (2.13). Whether the relationship is a significant one is then determined by carrying out a (non-linear) Wald-test of $\frac{\eta\delta-\theta\gamma}{(\delta+\gamma)^2}=0$.

Table 3 shows the estimated relationships between the CRI and various balance sheet variables (which are for the purpose of these table averaged over the entire sample period). Note that Table 3 essentially reports a number of univariate relationships since we run (2.11) for each variable and then compute its relationship with the CRI.

The first four variables in the table are traditional measure of banks' loan risk: non-performing loans, loan-loss provisions, loan-loss allowances, and net charge-offs (all four scaled by total loans). They all have the expected sign (positive) and are significant at the 1% level. Thus, banks whose balance sheet indicates that they have a lower loan quality also have a higher CRI, that is they are perceived by the market as having riskier exposures. We also note that these results represent strong and consistent evidence that the CRI captures general credit risk.

The next four variables represent common proxies of asset risk. The first variable considered is the bank's ratio of total risk-weighted assets to total assets, which turns out to be positively and significantly related to a bank's CRI. The second variable is loan growth, which has been found to explain asset risk at banks (see Foos, Norden and Weber (2010)). The idea behind this proxy is that a bank which wants to expand its loan volume quickly, presumably has to do so at the cost of accepting lower quality borrowers. This would suggest a positive relationship between loan growth (computed as the average loan growth over the sample period) and the CRI. The point estimate is indeed positive, however, the relationship is not significant. The next variable is the ratio of interest income from loans to total loans. This variable has a positive and significant relationship with the CRI. This is according to expectations as banks will tend to charge higher rates on riskier loans. A high interest rate income may hence indicate a risky loan portfolio. Finally, we consider a bank's return on assets (ROA). The a priori relationship of this variable with the CRI is ambiguous. On the one hand, banks may charge higher rates on riskier loans. On the other hand, riskier borrowers are also more likely to default. In addition, banks with poor management may have simultaneously risky loans and low profitability. The table shows that there is a negative and significant relation with the CRI. Thus the market perceives banks with high profitability to have a relatively safe loan portfolio.

The next set of variables contains three basic characteristics of banks' balance sheets: leverage, loan-to-asset ratio and size. First, it can be seen that there is a positive and significant relationship between a bank's leverage (as measured by the debt-to-asset ratio) and its CRI. An explanation for this may be different risk preferences at banks: a bank which follows a high risk strategy may jointly choose a high-risk loan portfolio and operate with high leverage. Note that since the CRI is a *relative* credit risk sensitivity, there is no mechanical relationship between the CRI and leverage which may arise from the fact that (everything else being equal) highly leveraged banks are more sensitive to changes in loan values. The same argument also applies to our next variable, the loan-to-asset ratio. This variable is found to be positively related to the CRI. A possible explanation for this relationship is similar to the loan growth argument. If a bank expanded its loan portfolio aggressively in the past, it might have been forced to compromise on the quality, thus leading to a positive correlation between the loan-to-asset ratio and high risk exposures. The last of the basic balance sheet characteristics we consider is size, measured by the log of total assets. We find that larger banks tend to have a lower share of high risk exposures. There are various interpretations of this. For one, small banks may simply operate in riskier local markets. It may also be that large banks have better risk management techniques, thus allowing them to reduce lending risk. Finally, there may also be difference in risk preferences among small and large banks.

The last two variables in Table 3 are a bank's share of real estate loans and a dummy for whether the bank securitizes such loans. The former variable is positively and significantly related to a banks' CRI. Hence banks with more real estate lending are perceived by the market as having worse credit portfolios. This result is consistent with the experience of the subprime crisis, which was driven by high risk mortgages. It also suggests, as discussed previously, that the CRI captures lending risk beyond corporate loans (which make up the CDS indices). Regarding the securitization dummy: we do not find that this variable is significantly related to lending risk as perceived by the CRI. This may indicate that securitization has two opposing effects on securitizing banks themselves. On the one hand, securitizing real estate loans may directly reduce high risk exposures at these banks. On the other hand, these banks may use the freed-up capital to extend new loans (for a theoretical analysis of this effect, see Wagner (2007) and Wagner (2008)). These loans are presumably riskier, for example, due to the incentive problems created by the securitization business.

It is an interesting question whether the established associations between the CRI and other bank variables are due to information unique to the CRI, or whether this information is already contained in standard measures of bank risk that can be generated from the stock market index. To test this, we rerun the above regressions controlling for bank betas. The results (not shown here) are almost identical to ones in Table 3, both in terms of coefficients and significance (the only noteworthy difference is that total risk weighted assets are now only significant at the 10% level). This suggests that the CRI captures information that is not already contained in risk measures obtained from the stock market index.

2.4.5 Using the CRI to Predict Bank Failures

The last section has shown that the CRI is related to various balance-sheet-based risk proxies. Naturally, the question arises if the CRI has informational value beyond these proxies. One way to test this is to see whether the CRI has predictive power in forecasting bank failures, controlling for other measures of bank risk. This would make the CRI an appealing indicator for regulators and supervisors. This section thus studies the forecasting ability of the CRI during our sample period. This period is well suited for such an exercise as it comprises the subprime crisis during which there were many bank failures.

The first step is the identification of failed banks. We start with the failed bank list of the FDIC[14] and take all failed commercial banks that belonged to one of our 150 bank holding companies. There are seven of such banks. In six out of seven cases the commercial bank's BHC also went bankrupt following the failure of its commercial bank. We thus identify six failed BHCs. To these we add two rescue mergers (Wachovia and National City) as these two BHCs would have very likely failed if they were not taken over with the direct help (Wachovia) or indirect help (National City) of the government or the Federal Reserve. This gives us a total of eight BHCs for our empirical analysis. A first inspection of their CRIs shows that the CRI may be useful in identifying bank failures: the average CRI of these banks one month before failure was 0.24 (compared to a sample mean of 0.17).

The empirical analysis is carried out by means of probit regressions. In each quarter the dependent failure variable takes the value of one if a bank fails in this quarter, while surviving banks are assigned a zero. Failed banks are dropped from the sample after the quarter of failure. Failure is then (dynamically) predicted using information one (or two) quarters prior to failure. Our sample starts with the start of the subprime crisis (second quarter of 2007) and ends in the last quarter of 2009. We estimate the following relationship

$$F_{i,t+k} = p(CRI_{i,t}, \mathbf{Z}_{i,t}), \tag{2.14}$$

where F is the bank-specific failure indicator, $\mathbf{Z}$ denotes as set of controls and $k = \{1, 2\}$ denotes quarters. We do not include bank fixed-effects because for all surviving banks there is no variation in the dependent variable and we would thus only look at variations within the group of failing banks. Note that (2.14) is based on quarterly variables. In some cases (this applies to the balance sheet variables) we did not yet have the data for the end of our sample. We then simply use the last available data. Note also that the CRI that is used as an explanatory variable in this regression is itself an estimated parameter. This may cause issues known as "generated regressor problems". However, we argue in Appendix B that in our specific setting these problems are unlikely to be important.

Table 4 reports the results for various sets of control variables. Panel A

[14] Available at http://www.fdic.gov/bank/individual/failed/banklist.html

contains the results for the two quarter forecasting, while Panel B the results for the failure forecasting by one quarter. Column 1 in each panel reports the regression without controls (thus only including the CRI). In column 2 we include traditional measure of loan risk. In columns 3 and 4 the CRI is tested alongside proxies for asset quality and general bank characteristics, respectively. Column 5 controls for real estate activities. The share price beta (estimated from separate regressions with only a non-orthogonalized stock index included) and the Z-score are considered in columns 6 and 7, respectively. Finally, column 8 reports the results when all controls are included.

Column (1) shows that the CRI is significant (at the 5% level) in explaining failures at both forecasting horizons, and is so with the expected (positive) sign. The coefficients are similar for both horizons, indicating stability of our specification. Across the different specifications in columns (2)-(8) the CRI is always significant for two quarter forecasting. For the one quarter forecasting the CRI is significant in all regressions, except in column (4), which includes leverage and bank size (note, however, that in the regression considering the full set of controls (column 8) the CRI is again significant, albeit weakly).

Focusing on the control variables, one can see in column (2) that the non-performing loans and the net charge-offs are only marginally significant in Panel A. The non-performing loans also have a counter-intuitive sign (which might be due to multicollinearity issues among the loan risk proxies). In Panel B, the net charge-offs turn insignificant while the non-performing loans increase in significance but again with a negative sign. In both panels column (3) shows that the return on assets is the only significant control variable and is so with a negative sign. Among the basic balance sheet characteristics in column (4) leverage and size are significant with a positive sign at both forecasting horizons. The results for leverage confirm the perception that many of the problems during the crisis of 2007-2009 were related to excessive debt-taking at banks. The size result is interesting, however, it should be noted that it is not very robust (when we exclude leverage, for example, size becomes insignificant)

Column (5) shows next that real estate loans only weakly relate to bank failures. This is surprising since real estate was at the root of the crisis, but the explanation may be that risk information coming from real estate exposures is already subsumed in the CRI. In addition, we can also see that the dummy for the securitization of real estate loans has no prediction power as it is insignificant in both panels. Column (6) shows the regression with the share price beta included. It can be seen that for each time horizon the beta is not significant (while the CRI remains significant). This finding suggests that the information contained in the CRI has forecasting power that is superior to measures obtained from the stock market index. Column (7) includes the Z-score as a control variable. The Z-score turns out to be highly significant in forecasting failure. This is expected since, by construction, it is designed to represent proximity to failure. However, for each time horizon we can see that the CRI stays significant. The CRI thus contains information that can forecast bank failures beyond the information contained in the distance-to-default measure. We have also tested a Merton-based distance-to-default measure as an alternative to the Z-score (not reported); the results are very similar but are a bit weaker for the one-quarter horizon.

Besides the CRI *level*, *changes* in a bank's CRI may potentially also contain information about failures. We thus have redone all regressions including the quarterly change in the CRI alongside the CRI (not reported here). The result is that these CRI changes are almost always insignificant, and when they are significant they are only weakly so and have the wrong sign (negative). The results for the CRI, however, do not change. These findings are consistent with our priors in that what should ultimately matter is the bank's current level of risk, and not how it changed relative to previous quarters.

Besides for our sample of BHC, we also do forecasting regressions for a wider set of banks. We started again from the failed bank list of the FDIC, which gives us in total 208 U.S. commercial banks that failed during our sample period. From these banks we exclude banks that have assets of less than one billion USD, which reduces the sample to 43 banks. From these banks we lose 18 since they are not listed on any stock exchange. We lose another 9 because either their shares very illiquid or their bank holding company survived the failure of the commercial bank. This leaves us with 16 failures, of which 6 are already included in our original sample of 150 large BHC. Adding the two rescue mergers gives us 18 bank failures. Their mean CRI one month before failure is 0.30 (comparing to a sample mean of

0.17). As for some of these banks we were not able to get all the balance sheet data (some banks are registered as Thrifts and have hence different reporting requirements) we focus in this exercise on probits with the CRI and the distance-to-default measure only.

Table 5, Panel A and B, contains the results. Column (1) in each panel shows the results with only the CRI included. The CRI turns out to be positively and very significantly related to future bank failures. The coefficients are very similar to the ones obtained for the smaller set of banks. Column (2) reports results with the Z-score included (the results for the Merton-based distance-to-default are similar). The Z-score is significant with the correct sign at the one-quarter horizon but insignificant at the longer forecasting horizon. The CRI is still significant and its coefficient even increases.

The marginal coefficients for the CRI are about 0.05 for both horizons. This implies that if a bank has a CRI that is 0.1 higher than its peers (for comparison, recall that the mean CRI is 0.167 and the standard deviation is 0.06), its probability of failing in the next quarter is 0.05x0.1=0.5% higher. Hence, over the entire sample period (which consists of 10 quarters), this means that the bank has a 5% higher chance of failing, which we consider to be economically significant.

The results from the larger set of banks corroborate our earlier findings that the CRI has significant power in predicting bank failures. The results notably even holds when controlling for measures that are designed to capture proximity to failure, namely the distance-to-default measures.

2.4.6 The CRI and Banks' Share Price Performance During the Subprime Crisis

In this section we address the question whether the CRI also has predictive power for the performance of banks during the subprime crisis, as measured by their share prices. The idea is the following. As discussed earlier, a high CRI is not necessarily a bad sign for bank management as long as the bank gets adequately compensated for the risk through higher interest rates. However, if there is an unexpected downturn in the economy, banks with higher CRIs should be harder hit since high risk exposures perform relatively worse when economic conditions deteriorate. Thus high CRI banks should see their share price decline more during the subprime crisis than low CRI banks.

In this section we thus study whether a bank's CRI prior to the crisis relates to its performance in the crisis. For this we consider again the same set of controls as in the previous section. In particular we are estimating the following cross-sectional regression:

$$perf_i = \alpha + \beta CRI_i + \boldsymbol{\gamma}\mathbf{Z}_i + \varepsilon_i, \tag{2.15}$$

where $perf_i$ is a bank's share price performance from June 15 2007 until June 15 2008, CRI_i is a bank's CRI calculated using information only up until June 15, 2007, and $\mathbf{Z}_i$ is the vector of control variables already discussed before. This time this vector is however constrained to information before June 15, 2007.

Table 6 reports the results using the same partitioning of controls as in Table 4. The main message is that the CRI is significantly and positively related to subprime performance and that this result is robust to the consideration of various controls. In fact, the CRI is always significant at least at the 10% level, but is mostly so at the 5% or 1% level. Its coefficient is also relatively stable, ranging from -13 to -22. The size of the coefficient suggests that the relationship is economically relevant. A coefficient of -20, for example, implies that an increase in a bank's CRI by 0.1 is associated with a share price performance that is 7% worse than its peers.[15] This is noteworthy since the subprime crisis was not only a crisis of asset quality but was also driven by liquidity and funding issues. It also confirms the expectation that in periods of crises (regardless of their origin) banks with lower asset quality should be significantly more affected.

We also note that the significant control variables have the expected signs. Among the traditional loan risk measures and proxies for asset risk (columns (2) and (3)), the loan loss allowances, and the interest income from loans both have a negative sign, suggesting that banks with a higher share of bad

[15] This number is obtained by transforming the absolute share price decline implied by a CRI change of 0.1 (=-20x0.1=-2) into a relative share price decline using the sample share price mean (=28.44).

credits suffered more during the subprime crisis. In column (4) we can see that banks with a higher loan-to-asset ratio experienced a higher share price decline. We can also see that larger banks performed worse as well, consistent with the notion that it was mainly those banks which engaged heavily in real estate securitization activities. This interpretation is confirmed by the results reported in column (5), which shows that banks with more real estate loans, and banks that securitize those loans, perform relatively worse. Column (6) shows that the share price beta is not significant. This confirms previous findings which suggested that the information contained in the CRI has forecasting power that is superior to measures obtained from the stock market index. Column (7) shows (contrary to the failure analysis in Table 4) that the Z-score has no predictive power.

Finally, column (8) reports the results when all control variables are included. Besides the CRI, only two of the fifteen control variables are significant at the 5% level. This confirms the importance of the CRI in explaining the subprime performance. We note that, in particular, all traditional loan risk proxies are insignificant. The only controls that remain significant are bank size and the share of real estate loans. These two are factors that played a specific role in the current crisis but are not general measures of bank risk. This is different from the CRI, which is not construed to reflect characteristics of the crisis.

Taken together, the analysis of the share price performance during the subprime crisis confirms our priors that the CRI measures exposure to an economic downturn and thus allows to predict how banks fare if such a downturn sets in.

2.5 Concluding Remarks and Discussion

In this paper we have developed a new measure of the quality of banks' credit portfolios. This measure is not restricted to the potential losses from defaulting loans but captures also credit risks from other sources. It includes exposures arising from a variety of bank activities, such as securitizations and credit derivatives. Since it is derived from market prices, it comprises information from a wide range of sources and can, moreover, reflect new developments quickly. The *credit risk indicator* (CRI) is arguably also an independent assessment of banks' risks since it should be difficult for banks to consistently manage their share price sensitivities.

The CRI is a natural indicator of how well banks might perform in periods of a worsening of credit risks in the economy. Indeed, we have found that the CRI could forecast the performance of banks during the subprime crisis. The CRI may thus be used by bank supervisors, alongside with other information, as a criterion for identifying potentially exposed institutions well before a downturn materializes. By contrast, as we have discussed in the paper, once a crisis materializes other indicators (such as the distance-to-default or the bank's CDS spread) should be preferred from a conceptual perspective. The CRI could also potentially serve as an input for the computation of risk weights for regulatory capital requirements. For example, if one (for argument's sake) assigns investment grade exposures a risk weight of zero and subinvestment grade exposures a weight of 100%, the CRI simply gives the average risk-weight of the banks' credit exposures. The CRI is thus an interesting alternative to the crude risk weights of the standardized approach of Basel I but also the advanced approach (where banks determine their own risk-weights) as it does not rely on assessments that are under the discretion of banks themselves. The CRI may also help bank creditors in gauging the riskiness of loans, as well as being useful for bank shareholders in assessing the ability of bank managers to make high quality investments.

The CRI may also help us in the future to better understand the factors that drive a bank's credit quality. Previous research, which has mostly focused on balance sheet data as a measure of credit quality, was constrained by the absence of comprehensive and independent measures of credit quality. We believe it may be interesting to use the CRI to study the influence of factors such as bank strategy (e.g., specialization, growth, relationship orientation), geographical location or corporate governance for credit quality. The CRI may also be of use for enhancing our understanding of how credit risk transfer activities at banks (such as securitizations or trading in credit derivatives) impact credit quality.

Our research also informs the current debate on the efficiency of financial markets. While prior to the subprime crisis the consensus probably was that markets overall work well in evaluating risks, the crisis has highlighted various apparent failures in that respect. Since the CRI measures the market's perception of the proportion of high risk exposures, it allows us to separate this dimension of potential market failure from the failure to anticipate changes in default risks overall in the economy. Our empirical results suggests that the market was well able to spot the composition of risks at banks but failed in the second dimension, that is, forecasting the deterioration in overall default rates in the economy during the subprime crisis. These findings add to the growing perception among academics and policy makers that markets may work reasonably well in the cross-section but may be more prone to failure when it comes to the forecasting of future economic conditions (and hence may fail to avoid the build-up of bubbles).

2.6 Tables

Table 1: Aggregate CRI

	Full Sample	1st subperiod	2nd subperiod	3rd subperiod
ΔS&P500(orth)	0.00120***	0.00138***	0.00125***	0.00109***
	(7.66e-06)	(1.25e-05)	(1.40e-05)	(1.09e-05)
Δ*CDS-XO*	-0.000563***	-0.000896***	-0.000682***	-0.000416***
	(9.22e-06)	(2.28e-05)	(1.68e-05)	(1.25e-05)
Δ*CDS-IG*(*orth*)	-0.00305***	-0.00387***	-0.00349***	-0.00281***
	(2.88e-05)	(0.000151)	(5.33e-05)	(3.37e-05)
Δ1-Month Interest Rate	-9.69e-05***	-8.48e-05***	-0.000102***	0.000296***
	(1.00e-05)	(1.97e-05)	(1.12e-05)	(4.69e-05)
Δ10-Year Interest Rate	0.000104***	0.000135***	0.000161***	8.73e-05***
	(1.43e-05)	(2.60e-05)	(2.84e-05)	(1.90e-05)
ΔInflation	-0.000628***	-0.000246***	-0.00135***	-0.000358***
	(2.44e-05)	(4.99e-05)	(6.38e-05)	(2.87e-05)
Constant	-0.000750***	-0.000537***	-0.00111***	-0.000728***
	(6.42e-05)	(8.70e-05)	(0.000138)	(0.000103)
Observations	148653	50513	50177	47963
R^2	0.345	0.266	0.355	0.398
CRI	0.1557	0.1879	0.1637	0.1289
95% Confidence Interval	0.1510 0.1603	0.1743 0.2014	0.1562 0.1712	0.1224 0.1354

The dependent variable is the daily change in the individual bank share price (normalized by its mean). The regression in column (1) is the one of equation (2.9). Columns (2) - (4) report the same regression for each third of the sample period. Note that the number of observations in the subsamples can differ because only observations are included where the stock of a bank is actively traded. In addition, failed banks drop from the sample mostly in the last subsample. Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 2: Descriptive Statistics for Individual CRIs

Variable	Observations	Mean	Median	Min	Max	St.Dev.
CRI	150	0.1670	0.1537	0.0546	0.4132	0.0561

Table 3: The Relationship between the CRI and Other Measures of Bank Risk

	Coeff.	SE
Non-Performing Loans/TL	4.402***	(0.461)
Loan Loss Provisions/TL	9.553***	(0.994)
Loan Loss Allowance/TL	7.698***	(1.036)
Net Charge Offs/TL	11.91***	(1.405)
Tot. Risk Weight. Assets/TA	0.185***	(0.0327)
Loan Growth	0.0561	(0.187)
Interest from Loans/TL	4.360***	(0.738)
ROA	-5.702***	(0.762)
Debt/TA	0.800***	(0.171)
Loans/TA	0.115***	(0.0325)
log(TA)	-0.00960***	(0.00250)
Real Estate Loans/TL	0.144***	(0.0225)
Dummy Sec. Real Est. Loans	-0.00438	(0.0100)

Reported is the coefficient of the non-linear Wald test on equation (2.13). TL= Total Loans; TA= Total Assets; Sec. = Securitization; ***, ** and * denote a significant relationship between the CRI and the corresponding variable at the 1%, 5% and 10% level respectively.

Table 4: Failure Prediction using the BHC Sample

Panel A: Failure in 2 Quarters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CRI	2.316**	1.720**	2.278***	1.495**	2.196***	2.599**	1.587***	2.070***
	(0.921)	(0.730)	(0.799)	(0.761)	(0.804)	(1.074)	(0.584)	(0.728)
Non-Performing Loans/TL		-4.820*						-8.177***
		(2.493)						(2.744)
Loan Loss Provisions/TL		-13.54						-15.49
		(20.42)						(20.27)
Loan Loss Allowance/TL		12.49						33.91
		(17.42)						(25.51)
Net Charge Offs/TL		50.01*						45.06**
		(25.99)						(19.68)
Tot. Risk Weight. Assets/TA			-0.810					-1.175
			(0.994)					(1.560)
Loan Growth			-5.352					4.105
			(6.653)					(6.721)
Interest from Loans/TL			4.865					-10.17
			(8.954)					(9.071)
ROA			-10.76***					-0.685
			(3.385)					(5.168)
Debt/TA				17.68***				8.300
				(5.989)				(8.174)
Loans/TA				1.380				1.991
				(0.979)				(1.913)
log(TA)				0.195**				0.500***
				(0.0874)				(0.156)
Real Estate Loans/TL					2.269*			3.800***
					(1.201)			(1.054)
Dummy Sec. Real Est. Loans					0.181			-0.798
					(0.308)			(0.525)
Beta						0.298		-0.0295
						(0.232)		(0.217)
Z-score							-0.201***	-0.0688
							(0.0524)	(0.0851)
Constant	-3.035***	-3.475***	-2.445***	-23.21***	-4.827***	-3.543***	-1.344***	-21.82***
	(0.216)	(0.346)	(0.861)	(5.865)	(0.980)	(0.463)	(0.415)	(8.341)
Observations	1479	1479	1479	1479	1479	1479	1479	1479
pseudo R^2	0.0584	0.231	0.153	0.190	0.112	0.0732	0.186	0.374

The dependent variable is the bank specific failure indicator for each quarter. All regressions are based on equation (2.14). Clustered standard errors (at the bank level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 4: Failure Prediction using the BHC Sample

Panel B: Failure in 1 Quarter

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CRI	2.181**	1.658**	2.077***	1.160	2.052***	2.547**	1.361**	1.740*
	(0.872)	(0.729)	(0.707)	(0.788)	(0.762)	(1.059)	(0.529)	(1.002)
Non-Performing Loans/TL		-6.120**						-8.920***
		(2.792)						(2.896)
Loan Loss Provisions/TL		-3.371						-3.114
		(26.00)						(26.92)
Loan Loss Allowance/TL		11.10						26.78
		(17.39)						(28.31)
Net Charge Offs/TL		42.44						29.29
		(31.10)						(27.16)
Tot. Risk Weight. Assets/TA			-0.737					-0.726
			(1.049)					(1.661)
Loan Growth			-5.835					5.619
			(6.835)					(6.301)
Interest from Loans/TL			11.28					-3.043
			(8.605)					(7.875)
ROA			-10.93***					0.754
			(3.421)					(4.489)
Debt/TA				19.21***				10.99
				(6.072)				(7.010)
Loans/TA				1.484				2.123
				(1.003)				(2.061)
log(TA)				0.198**				0.501***
				(0.0898)				(0.166)
Real Estate Loans/TL					2.276*			3.617***
					(1.193)			(1.189)
Dummy Sec. Real Est. Loans					0.174			-0.919*
					(0.307)			(0.553)
Beta						0.391		0.184
						(0.275)		(0.238)
Z-score							-0.229***	-0.125
							(0.0524)	(0.105)
Constant	-3.002***	-3.516***	-2.835***	-24.67***	-4.796***	-3.682***	-1.120***	-24.77***
	(0.206)	(0.322)	(0.945)	(6.063)	(0.966)	(0.539)	(0.420)	(8.003)
Observations	1479	1479	1479	1479	1479	1479	1479	1479
pseudo R^2	0.0491	0.249	0.174	0.196	0.103	0.0776	0.209	0.394

The dependent variable is the bank specific failure indicator for each quarter. All regressions are based on equation (2.14). Clustered standard errors (at the bank level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 5: Failure Prediction with Enlarged Sample

	Panel A		**Panel B**	
	Failure in 2 Quarters		Failure in 1 Quarter	
	(1)	(2)	(1)	(2)
CRI	2.118***	3.002***	2.182***	3.010***
	(0.634)	(1.011)	(0.678)	(1.126)
Z-score		-0.0659		-0.111**
		(0.0403)		(0.0526)
Constant	-2.737***	-2.361***	-2.753***	-2.015***
	(0.162)	(0.407)	(0.171)	(0.551)
Observations	1546	1546	1546	1546
pseudo R^2	0.0703	0.126	0.0757	0.162

The dependent variable is the bank specific failure indicator for each quarter. All regressions are based on equation (2.14). Clustered standard errors (at the bank level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 6: Subprime Share Price Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CRI	-17.44**	-21.70***	-16.24*	-13.04**	-21.07***	-16.01*	-16.75**	-22.03**
	(7.206)	(7.877)	(8.742)	(6.124)	(7.449)	(8.985)	(7.050)	(9.845)
Non-Performing Loans/TL		33.60						142.3
		(110.7)						(184.0)
Loan Loss Provisions/TL		-8,740						-8,423
		(8,555)						(9,317)
Loan Loss Allowance/TL		-1,113*						-1,152
		(574.7)						(698.5)
Net Charge Offs/TL		8,891						11,933
		(8,987)						(11,179)
Tot. Risk Weight. Assets/TA			-27.16					-18.91
			(21.34)					(18.07)
Loan Growth			-37.14					0.525
			(27.98)					(36.31)
Interest from Loans/TL			-382.8					-343.8
			(565.9)					(610.4)
ROA			-2,225*					-2,599
			(1,325)					(1,754)
Debt/TA				-0.880				-20.67
				(65.62)				(119.9)
Loans/TA				-43.66**				-9.408
				(17.57)				(19.93)
log(TA)				-4.667***				-3.744***
				(0.682)				(1.264)
Real Estate Loans/TL					-17.84**			-20.29**
					(8.065)			(8.633)
Dummy Sec. Real Est. Loans					-16.31**			-11.54
					(7.495)			(9.159)
Beta						2.821		-5.828
						(6.368)		(5.763)
Z-score							0.625	-0.697
							(0.730)	(1.158)
Constant	-7.805***	7.663	46.79***	95.51*	8.869	-11.74	-13.46*	171.3
	(2.105)	(7.326)	(16.90)	(54.69)	(5.629)	(8.681)	(7.101)	(118.0)
Observations	150	150	150	150	150	150	150	150
R^2	0.014	0.065	0.099	0.107	0.110	0.016	0.020	0.254

The dependent variable is an individual bank's share price decline over the period 15 June 2007 until 15 June 2008. All regressions are based on equation (2.15). Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

2.7 Figures

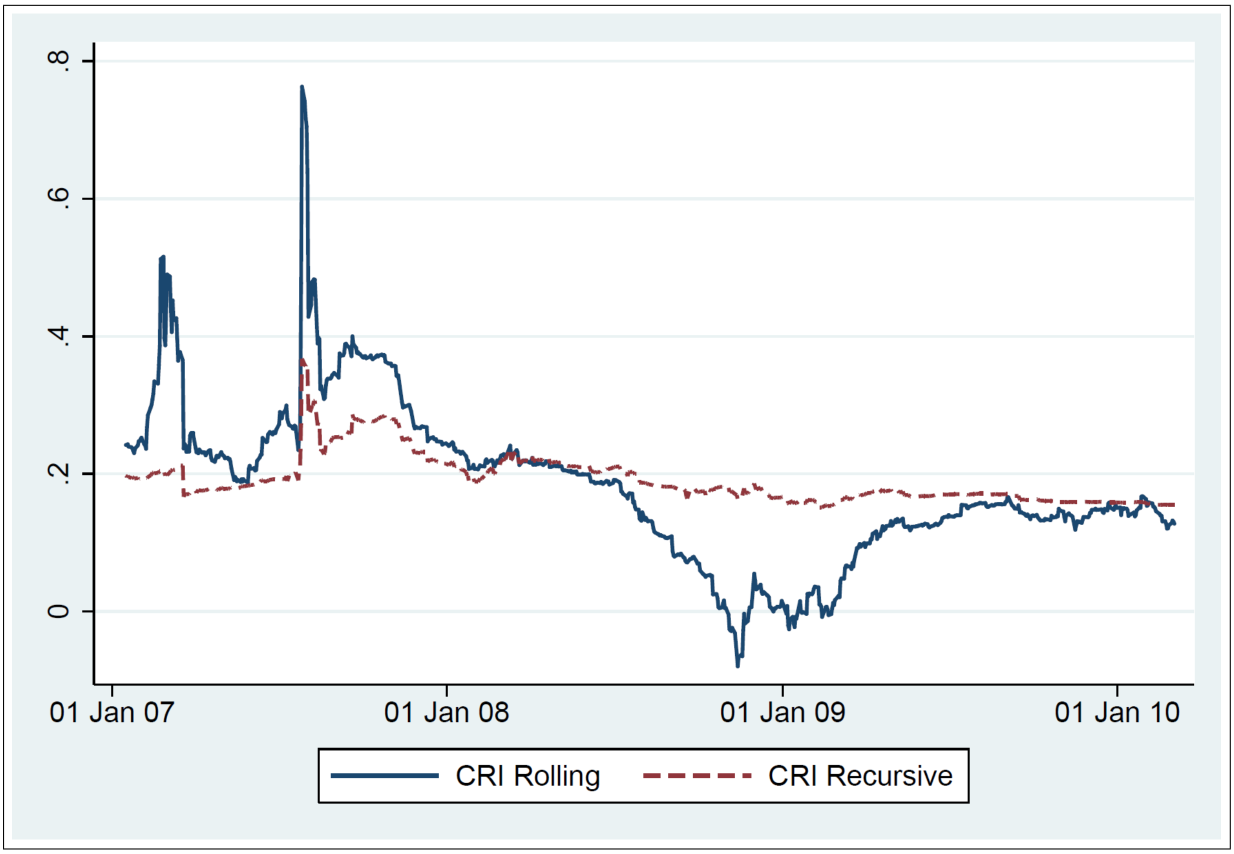

Figure 1: Rolling and Recursive Window Analysis of the Aggregate CRI

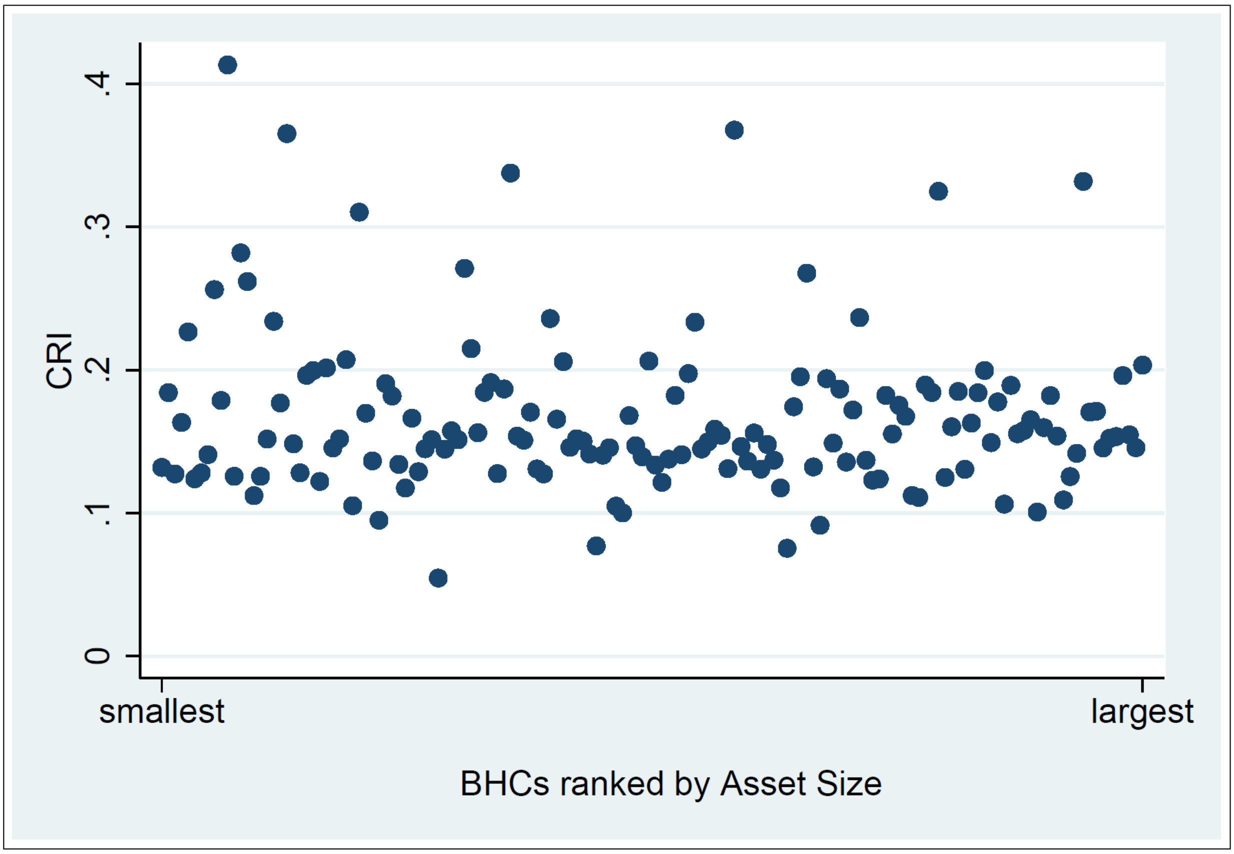

Figure 2: Scatterplot of Individual CRIs

2.8 Appendix A: Non-Linear Relationship between the Value of Loans and the Value of Bank Equity

The model in Section 2.3 presumes that changes in the value of a bank's loan portfolio translate one-to-one into changes in the bank's equity (in equation (2.5) we have $\frac{\partial V(E)}{\partial V(Loans)} = 1$). This may not always be the case. In particular, the one-to-one relationship will break down if there is an option value of equity (as predicted by the Merton-model) or due to bailout expectations. Suppose now instead that we have more generally $V(E) = f(V(Loans))$, where f is a continuous and monotonically increasing function but not constrained to be linear. The function f may also depend on other bank characteristics, such as its asset risk. Using equation (2.6), we can obtain a first-order approximation of $\triangle p$ caused by changes in the value of loans:

$$\begin{aligned}\triangle p &\approx f'(V(Loans))\left(-H \triangle CDS^H - L \triangle CDS^L\right)\\ &= -H \cdot f'(V(Loans)) \triangle CDS^H - L \cdot f'(V(Loans)) \triangle CDS^L \qquad (2.16)\end{aligned}$$

The γ and δ estimated from equation (2.7) will hence be equal to $\gamma = -H \cdot f'(V(Loans))$ and $\delta = -L \cdot f'(V(Loans))$. Thus, if we compute the CRI according to equation (2.8) we still obtain the share of high-risk loans:

$$CRI = \frac{\gamma}{\gamma+\delta} = \frac{-H \cdot f'(V(Loans))}{-H_i \cdot f'(V(Loans)) - L \cdot f(V(Loans_i))} = \frac{H}{H+L}. \qquad (2.17)$$

The reason for this result is as follows. Depending on bank characteristics, the value of equity may display different sensitivities to the value of the loan portfolio. Consequently, the sensitivities to changes in the value of high risk and low risk loans will change as well. However, these sensitivities will change precisely by the same factor, and since the CRI is a measure of relative sensitivities, the effect cancels out.

2.9 Appendix B: Generated Regressors

Since we are using two stages in our analysis (in the first we estimate CRIs at the bank level, which we later include in the second stage as regressors), our analysis may suffer from generated regressor problems (see, for example, Pagan, 1984). While replacing a regressor with its estimate in an OLS regression causes no problems for consistency (Wooldridge, 2002, p.115), it might do so for inference. This is because the standard errors obtained are often invalid as they ignore the sampling variation of the estimated regressor. However, this problem should not apply in our setting since we use different dimensions in each stage: in the first stage we use the time dimension t (which ranges from 1 to 1025) to obtain CRI estimates at the bank level, while in the second stage we use the cross-sectional dimension i (ranging from 1 to 150). Since our time dimension is large both in an absolute sense and relative to the cross-sectional dimension (almost seven times larger), asymptotic theory can be applied here. Based on this theory, the CRIs estimated in the first step should be asymptotically precise so that we can draw valid statistical inferences from it when using it in the second stage of our regression.

Chapter 3

Measuring the Tail Risks of Banks

3.1 Introduction

The recent financial crisis has demonstrated again that a systemic banking crisis, a situation in which many banks are in distress at the same time, can induce large costs for the economy. The task of supervisors and regulators is to avoid and mitigate, as far as possible, such crises. For this they need advance information about how banks are exposed to shocks to the economy. This allows them to identify weak banks and put them under increased scrutiny but also to monitor general risks in the financial system. When evaluating the exposure of banks it is also of paramount importance to distinguish between exposures to normal market shocks, and exposures to large shocks. For example, a financial institution that follows a tail risk strategy (such as writing protection in the CDS market) may appear relatively safe in normal periods as it earns steady returns but may actually be very vulnerable to significant downturns in the economy.

Currently, supervisors and regulators obtain their information to a large extent from information generated by the bank itself, such as its accounts. While these sources are a crucial ingredient of the evaluation process they are not free from drawbacks. For example, most of this information is under the discretion of banks and may be used strategically[1]. Moreover, this data is typically backward looking and available only at relatively low frequency. Accounting information also misses important aspects such as informal knowledge (e.g., CEO reputation) or information contained in analysts' reports.

In recent years there has been growing interest in using market-based measures of bank risk. This is on the back of evidence that market signals contain valuable information about banks' risks (see Flannery (1998) and Flannery (2001) for surveys). While some of these measures focus on individual bank risk (such as Moody's KMV), others explicitly take into account the systemic aspect (e.g., Hartmann et al. (2006), Straetmans et al. (2008), De Jonghe (2009) and Adrian and Brunnermeier (2009)). These methods have in common that they essentially use information from historical tail risk events to compute *realized* tail risk exposures over a certain period.

This paper differs from these approaches in that we develop a forward-looking measure of bank tail risk. We define a bank's (systemic) tail risk as its exposure to a large negative market shock. We measure this exposure by estimating a bank's share price sensitivity to changes in far out-of-the-money put options on the market, correcting for market movements themselves. As these options only pay out in very adverse scenarios, changes in their prices reflect changes in the perceived likelihood and severity of market crashes. Banks that show a high sensitivity to such put options are hence perceived by the market as being severely affected should such a crash materialize. As this sensitivity reflects perceived exposures to a hypothetical crash, it is truly forward-looking in nature. This property is important to the extent that bank risks change quickly and hence historical tail risk exposures become less informative. Another advantage of this method is that it does not require the actual observation of any crashes, as the method relies on changes in their perceived likelihood.

We use our methodology to estimate tail risk exposures of U.S. bank holding companies. We find that the estimated exposures are inversely related

[1] For evidence on such strategic use see, for example, Wall and Koch (2000) and Hasan and Wall (2004) for the reporting of loan losses and Laeven and Majnoni (2003) for the provisioning of loan losses. Huizinga and Laeven (2009) also provide evidence that banks have used accounting discretion to overstate the value of their distressed assets in the current crisis.

to their CAPM beta. This seems a very interesting result with potentially important implications for financial regulation as it suggests that banks that appear safe in normal periods actually tend to be the banks that are most exposed to crashes. This may be because such banks follow tail risk strategies. We also compare our measure to a common measure of bank tail risk: the tail risk beta, which is obtained through quantile regressions. We find that both measures are fairly uncorrelated and hence provide different information. A potential explanation for this lies in the backward-looking nature of the tail risk beta and the fact that its estimation relies on observing (rare) tail risk events.

We also use our methodology to characterize the main drivers of bank tail risk. Understanding these drivers is important for regulators as it gives them information about which activities should be encouraged and which not. There is so far very little research on this question (a notable exception is De Jonghe (2009)). Our main findings are that variables which proxy for traditional banking activities (such as lending) are associated with lower perceived tail risk. Several non-traditional activities, on the other hand, are perceived to contribute to tail risk. In particular, we find securities held for-sale, trading assets and derivatives used for trading purposes are associated with higher tail risk. These findings are consistent with observed experience in the current crisis. Interestingly, securitization, asset sales and derivatives used for hedging are not associated with an increase in tail risk exposure. This indicates that a transfer of risk itself is not detrimental for tail risk, but that non-traditional activities that leave risk on the balance sheet are. On the liability side we find that leverage itself is not related to tail risk but that large time deposits (which are typically uninsured) are. We also find that perceived tail risk falls with size, which is indicative of bail-out expectations due to too-big-to-fail policies.

The remainder of this paper is structured as follows. In Section 3.2 we briefly review existing measures of tail risk. Section 3.3 develops the methodology for measuring tail risk exposure using put option sensitivities. Section 3.4 presents the empirical analysis. Section 3.5 concludes.

3.2 Existing Tail Risk Measures

The Value-at-Risk (VaR) has for many years been the standard measure used for risk management. VaR is defined as the worst loss over a given holding period within a fixed confidence level[2]. A shortcoming of the VaR is that it disregards any loss beyond the VaR level. The expected shortfall (ES) is an alternative risk measure that addresses this issue. The ES is defined as the expected loss conditional on the losses being beyond the VaR level. Another frequently used measure is Moody's KMV. Essentially, Moody's KMV is a distance to default measure that is turned into an expected default probability with the help of a large historical dataset on defaults. The distance to default is measured as the number of standard deviations by which the expected asset value exceeds the default point. A firm's one year expected default probability is then calculated as the fraction of those firms in previous years, which had the same distance to default and actually defaulted within one year.[3]

While these measures focus on individual bank risk, there has been a growing interest in recent years in systemic measures of bank risk. One strand of the literature focuses on tail-betas (e.g., De Jonghe (2009)). This concept applies extreme value theory to derive predictions about an individual bank's value in the event of a very large (negative) systematic shock. Loosely speaking, this method uses information from days where stock market prices have fallen heavily and considers the covariation with a bank's share price on the same day. It thus focuses on realized covariances conditional on large share price drops. A difficulty encountered when applying this method is that tail risk observations are rarely observed, and hence a large number of observations are needed to get accurate estimates (De Jonghe (2009) suggests at least six years of daily data).

Acharya et al (2008) develop a measure similar to the concept of market dependence, which is based on expected shortfalls instead of betas. They

[2] See Standard & Poors (2005) for a brief overview and Jorion (2006) for a more detailed approach.

[3] (Subordinated) debt and CDS spreads are an alternative and attractive measure of a bank's default risk. A shortcoming of these measures is that these spreads are not available for many banks (in the case of CDS spreads) and often not very liquid (in the case of bonds).

propose measuring the Marginal Expected Shortfall (MES), which is defined as the average loss by an institution when the market is in its left tail. Adrian and Brunnermeier (2009) consider a different aspect of systemic risk. They estimate the contribution of each institution to the overall system risk. A bank's CoVaR is defined as the VaR of the whole financial sector conditional on the bank being at its own VaR level. The bank's marginal contribution to the overall systemic risk is then measured as the difference between the bank's CoVaR and the unconditional financial system VaR. An advantage of the CoVaR is that it is relatively simple to estimate, as it is based on quantile regressions. In terms of its informational properties it is similar to the tail risk beta in that it focuses on realized tail risk.

Our measure is most similar to the tail risk betas as we also measure bank exposures to large market swings. A difference that is important for the interpretation of the estimates, however, is that while the tail risk beta relates to large daily market drops, we estimate exposures to a large prolonged downturn in the market (e.g., several months).

3.3 Measuring Tail Risk Using Put Options Sensitivities

In this section we present our methodology for measuring banks' tail risk exposures. We define the latter to be the bank's exposure to a general market crash (that is, a severe downturn in the economy). If the market crashes, a bank may suffer large, simultaneous losses on its assets, which may push it close to or into bankruptcy. Crucially, the extent to which it is exposed to crashes may differ from its normal market sensitivity. Consider two banks, A and B. Bank A invests mostly in traditional banking assets such as, for example, loans to businesses and households. Moreover, it invests in assets that are mainly exposed to normal period risk, such as, for example, junior tranches of securitization products (which lose value for modest increases in defaults, but are insensitive to defaults that go beyond the first loss level). In addition to these assets, bank A insures itself against default by buying protection on its assets (such as by buying credit default swaps on its loans).

Bank A's equity value will thus move more with the market in normal periods than in times of crisis.

Bank B, by contrast, follows a different business strategy. It does have traditional assets such as, for example, loans. However, in addition, it also follows investment strategies that return a small and steady payoff in normal periods but incur catastrophic losses when the market crashes. Examples for this would be selling protection in the credit default swap (CDS) market or buying senior tranches of securitization products, which lose value only when all other tranches have already incurred a total loss. Thus, even though bank B's equity value may behave similarly to bank A's in normal periods, it tends to fall relatively more when the market crashes. This scenario is depicted in Figure 1, where bank A performs better in crash times (market values below $\overline{x}$) than bank B, even though in normal periods equity values are similarly distributed.

We next describe our method for measuring a bank's tail risk exposure. For this suppose that there is a representative firm in the economy (which we interpret as the market). This firm exists for one period only and its (stochastic) next period equity value is denoted with x. Similarly, consider a bank with next period equity value y. We assume for the relationship between equity values of the bank and the market:

$$y(x) = \begin{cases} x^{\beta} & \text{if } x \geq \overline{x} \\ \frac{x^{\beta}}{(\frac{\overline{x}-x}{\overline{x}}+1)^{\gamma}} & \text{if } x < \overline{x} \end{cases} \tag{3.1}$$

When $x \geq \overline{x}$, the bank's equity value is thus identically distributed to that of a firm with a beta of β. However, for $x < \overline{x}$, the bank's equity value additionally depends on the relative shortfall of the market to $\overline{x}, \frac{\overline{x}-x}{\overline{x}}$ $(\in [0, 1])$. For $\gamma > 0$ its equity value will be more sensitive to the market, hence the bank has tail risk over and above the normal period exposure, while for $\gamma < 0$ we have the opposite case. Only in the case of $\gamma = 0$ does the bank's tail not differ from its normal period risk.

Since tail risk realizations ($x < \overline{x}$) are rarely observed, our estimation relies on changes in perceived tail risk, which we will measure through changes in put options prices. For this consider a put option with strike price $\overline{x}$ that is deep out-of-the-money ($\overline{x}$ is hence a tail risk realization). We have for the pay-off from this put

$$p(x) = \begin{cases} 0 & \text{if } x \geq \overline{x} \\ \overline{x} - x & \text{if } x < \overline{x} \end{cases} \tag{3.2}$$

Inserting into (3.1), totally differentiating wrt. y and dividing by y yields

$$\frac{dy(x)}{y} = \beta \frac{dx}{x} - \gamma \frac{dp}{p + \overline{x}}. \tag{3.3}$$

Percentage changes in the bank's equity values ($\frac{dy(x)}{y}$) thus relate to percentage changes in the market ($\frac{dx}{x}$), giving the standard β-effect. Additionally, they also relate to relative changes in the value of the option, $\frac{dp}{p+\overline{x}}$[4], arising from tail risk exposure.

In our empirical implementation we will identify tail risk sensitivities by adding a put option (on the market) to a standard market regression and interpreting the sign of the put option coefficient. Tail risk sensitivities will thus be estimated through changes in put option prices (that is, changes in expected market crash likelihood and severity).[5]

3.3.1 A Discussion of the Methodology

We believe that our methodology has several attractive features. First, the method is forward-looking in nature, that is, it captures *expected* tail risk exposure at banks. This contrasts with other popular methods for measuring tail risk, such as tail risk betas or the CoVAR. These methods essentially

[4]The correct term here is indeed $\frac{dp}{p+\overline{x}}$ and not, as one might think, $\frac{dp}{p}$. The bank-market relationship consistent with $\frac{dp}{p}$ would be $y = \frac{x^\beta}{(\overline{x}-x)^\gamma}$ for $x < \overline{x}$ as one can easily verify, which is not a sensible one as for $x = \overline{x}$ the denominator would then be infinite. Intuitively, the reason we need to correct for $\overline{x}$ is that otherwise for a put option with a low p, small changes in tail risk would translate into large *relative* put option changes.

[5]The estimation of γ is akin to estimating the factor-loadings in the asset pricing literature (see, for instance, Ang et al. (2006) and the references therein). While in the asset pricing literature the factor loadings are used in a second step to predict returns, we are interested here in the cross-sectional distribution of the factor-loadings. More precisely, we propose using the cross-sectional variation to identify banks that are perceived as being prone to a market crash.

compute correlations (or covariation) of banks with the market (or other banks) at days of large share price drops. They thus draw inferences from historical tail risk distributions and hence measure realized tail risk. The difference between forward and backward-looking measures is likely to be limited when banks only undergo small changes in their risks over time, but is potentially important in a dynamically evolving financial system.

Second, our measure identifies banks' tail risk exposure through *changes in expected* market tail risk, as measured by put option prices. This has the advantage that for our estimation we do not need tail risk events to actually materialize. Such events, by definition, occur only very infrequently and hence it is difficult to estimate their properties. Existing measures that rely on the historical distribution of tail risk events reduce this problem by relying on a large time series and by looking at modest tail risk realizations that occur more frequently. Our method allows the measurement of exposure to extreme forms of tail risk (for this one simply includes a very far out-of-the-money put option) and we can also estimate tail risk exposures using relatively short horizons.[6]

Since we measure exposures to market crashes, our measure captures *systemic* tail risk exposure. This is desirable since externalities from banking failures are typically associated with systemic crises, and not isolated bank failures. It should, however, be kept in mind that a bank that has a low estimated systematic tail risk may still be individually very risky to the extent that it pursues activities that are uncorrelated with the market. Finally, it should be noted that our measure, as other market-based measures, is net of any bailout expectations. If, for example, markets anticipate that governments may bail out certain banks, for example because they are too-big-to-fail, then these banks may have a low perceived tail risk, even if their underlying activities are relatively risky.

[6] Another attractive feature of our measure is that it is very easy to compute, as one simply has to run a market regression amended for a (market) put option.

3.4 Empirical Analysis

3.4.1 Data

We collect daily data on bank share prices and the S&P 500 (our proxy for the market) for the period October 4^{th} 2005 until September 26^{th} 2008 from Datastream. Put option data on the S&P 500 (more details will follow below) for the same period is from IVolatility.[7] In addition, various balance sheet data are collected from the FR Y-9C Consolidated Financial Statements for Bank Holding Companies (BHCs). We focus on U.S. BHCs which are classified as commercial banks and for which data is fully available. We focus on the BHC instead of the commercial bank itself, as typically it is the BHC that is listed on the stock exchange. Excluded are those banks whose share price change is zero in more than 10% of the cases in order to mitigate illiquidity issues. Foreign banks (even when listed in the U.S.) and pure investment banks are also excluded. The final sample contains 209 Bank Holding Companies.

An important question is the choice of the option strike price. Ideally we would choose options such that on each day they represent the same crash probability. Taking an option with the same strike price each day is hence not desirable, as market prices change over time and an initially out-of-the-money option may become an in-the-money option (this is precisely what would have happened over our sample period). Taking the strike price to be a (fixed) fraction of the S&P500 is also not a good solution as this ignores that the likelihood of tail risk realizations is also driven by the volatility. We hence decided to choose options such that their price does not vary over time, that is we adjust the option's strike price each day such that its (previous day) price stays the same. For this we use an option price of 0.5 (50 cents), which translates into an implied strike that was on average 33% below the S&P 500 during our sample period[8].

[7] We also considered using put options on a banking index (the BKX index) instead of the market. There are two major disadvantages to this. First, the banking sector index in itself will already reflect tail risk in the financial system, thus the interpretation of the γ-estimates is not straightforward. Second, put option prices on the index are fairly illiquid.

[8] In the more tranquil (low volatility) times of 2006, the average implied strike was still

In order to compute the option price change for, say day 1, we proceed as follows. We first identify among all traded options the strike prices that give day 0 prices closest to 0.5. We then calculate the weight that makes their average price 0.5. Given this weight, we calculate the weighted average of their prices at day 1 and calculate from this the change of the price, dP, from day 0 to day 1. We thus compute price changes of options whose (hypothetical) strike price varies from day to day.

We initially considered all out-of-the-money puts. A first inspection, however, revealed that the 100er strikes (i.e. 500, 600, 700 etc.) are much more liquid than put options with other strike prices. We therefore use only these puts. For each day an option's strike price and its price change are then calculated according to the procedure described above. In order to mitigate the influence of changes in the remaining time to maturity on our analysis, we use for this an "on-the-run" series, where each quarter we jump to a more recently issued option with longer maturity. As a result, the remaining time to maturity is limited to an interval of between three and six months.

3.4.2 Estimated Tail Risk Exposures

We estimate equation (3.3) for each bank. For this the independent variable is winsorized at the 2.5% level. Figure 2 shows the tail risk estimates (gammas) plotted against bank size. It can be seen that there is considerable variation among the bank's gammas. There also seems to be a pattern of large banks having lower tail risk.

An important first question is whether our tail risk measure really adds anything in terms of informational content to the normal beta. For example, it may simply be that banks with large tail risk also have large beta. In this case, estimating the tail risk beta separately is of little value. Figure 3 plots banks' gammas against betas. The scatter plot shows that this concern is not justified. In fact, there is a strong negative relationship between beta and gamma. This suggests that the banks that appear safe if judged by their beta, are actually the ones that have a high tail risk.

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around 28% below the S&P 500 while after June 2007 it was on average around 38% below the S&P 500.

What can explain this negative correlation between normal period and tail risk? One explanation is so-called tail risk strategies, which produce steady returns in normal periods but actually expose the banks to severe downturns. For example, an institution that writes protection in the CDS market receives in normal periods a steady stream of insurance premia. However, in a significant recession many exposures will simultaneously default and large losses may materialize. Many trading strategies, such as the ones exploiting apparent arbitrage relations, create similar pay-off distributions. Another explanation for this negative correlation is that highly profitable institutions that operate in risky environments protect their franchise, for example by buying protection in the CDS market or by imposing a less fragile capital structure.

We are also interested in how our measure of tail risk relates to other measures of tail risk. An easy to implement measure is quantile-betas, which are obtained by running quantile regressions for an otherwise standard beta equation (see for example Koenker and Basset (1978) and Koenker and Hallock (2001)). In our context, we are of course interested in the lower quantiles in such a regression.

Figure 4a shows estimated quantile-betas obtained at the 5^{th} quantile plotted against our gamma. A negative relationship is detectable, which is surprising. However, it can be explained by considering Figure 4b, which plots the quantile-betas against normal betas. We can see that there is a very strong positive relationship. The likely cause is that the 5^{th} quantile does not represent sufficiently extreme risk and hence may not differ that much from normal period risk. And since we already know that normal beta and gamma are negatively correlated, this explains the direction of the relationship in Figure 4a.

We repeat the exercise at the 1^{st} quantile but the results (not reported here) are similar. Only when we move to the 0.1^{th} quantile (that is lowest 0.1% of the distribution) does the informational content of the quantile-betas differ from the CAPM betas. Figures 5a and 5b show the results. Figure 5a shows that there is no longer a negative relationship between our gamma and the quantile beta, and Figure 5b shows that there is also no longer a relationship with the standard beta.

Even though a negative correlation between the two tail risk measures is now absent, it is still surprising that there is no positive relationship between these measures. They thus seem to pick up different information. One difference between the methods is obviously that one is backward - and the other forward-looking. More importantly, however, there is also a conceptual difference. The quantile regressions capture tail risk as measured by large *daily* price changes. In this respect, an institution has a large tail risk beta if it moves a lot on days where the market drops a lot. This is different from our gamma, which intends to capture the comovement in case the market crashes over a period of three to six months (the average maturity of our put options). Arguably, for financial stability considerations the latter information is more relevant as large daily market drops (which may occur for example in a boom) do not necessarily result in stability issues. By contrast, a prolonged market downturn is likely to cause substantial problems at banks.

This conceptual difference may explain why the correlation among the measures is low. Consider for example a financial institution that follows a tail risk strategy by writing protection in the CDS market. This bank will be vulnerable to a severe downturn in the economy, as discussed earlier, and will hence have a high estimated gamma. However, the institution will not be very sensitive to large daily share price fluctuations as long as the downturn has not set in. Hence, it may have a low quantile-beta.

3.4.3 Determinants of Bank Tail Risk

In this section we are studying whether and how a bank's business activities relate to its tail risk. The most obvious way to do this is by regressing (estimated) gammas upon a number of balance sheet variables that represent various banking activities. This two step method has two disadvantages. First, it creates the problem of generated regressors (Pagan, 1984) and second, the estimation is not efficient as information from the first step (estimating the gammas) is not used in the second step.

For these reasons we employ a method which enables us to (efficiently) estimate the relationship in one step[9]. For this we amend equation (3.3) to

[9] The two-step method, however, yielded very similar results.

allow a bank's put option sensitivity to vary with a certain bank activity, say B. Since this interaction effect could be potentially non-linear in the activity, we express B relative to its sample mean ($\hat{B}$). In addition, we also interact the S&P 500 return with the balance sheet variable B to take into account that general market sensitivities may also differ depending on bank activities. We obtain the modified equation:

$$\frac{dy(x)}{y} = \alpha + (\beta + \theta(B - \hat{B}))\frac{dx}{x} - (\gamma + \delta(B - \hat{B}))\frac{dp}{p + \overline{x}}. \qquad (3.4)$$

The coefficient δ in this equation gives us the relationship between a bank's gamma and activity B (the equivalent of the coefficient of a regression of estimated gammas on B), evaluated at the mean. Since we are interested in several determinants of bank tail risk, we employ a multivariate variant of equation (3.4):

$$\frac{dy(x)}{y} = \alpha + (\beta + \sum \theta_j(B_j - \hat{B}_j))\frac{dx}{x} - (\gamma + \sum \delta_j(B_j - \hat{B}_j))\frac{dp}{p + \overline{x}}, \quad (3.5)$$

where j represents the respective bank activity.

Table 1 presents the balance sheet coefficients δ from a set of pooled regressions that are based on equation (3.5). The first column contains the results from a regression with some basic bank characteristics: size (measured by the log of total assets), the loan-to-asset ratio and the leverage ratio (measured by the debt-to-asset ratio). Size is negatively related to tail risk exposure. This may indicate that markets perceive large banks as being too-big-to-fail (TBTF). The loan-to-asset ratio is also negatively related to a bank's tail risk exposure. This finding is in line with other recent findings: both De Jonghe (2009) and Demirguc-Kunt and Huizinga (2009) find that traditional banking activities are less risky than non-traditional activities. The last variable considered is the leverage ratio. Although a higher leverage ratio is often associated with more default risk, it does not come out significant here (we return to this issue later).

Column two focuses on banks' lending activities by including proxies for loan quality and profitability. Among the loan quality proxies only the loan growth variable is significant, indicating a positive relationship with tail risk. This is consistent with the idea that a bank may only grow faster at the cost of lowering lending quality, and hence may become more exposed in a downturn[10]. We also find that a higher interest rate on the loans is associated with less tail risk, which can be explained by the fact that this indicates a higher profitability of banks, thus exposing it less to a crash in the market. Additionally, we include the return of assets (ROA) to capture the returns from other (partly non-traditional) asset activities. We find a positive relationship with tail risk, which is consistent with other recent findings (e.g., Demirguc-Kunt and Huizinga (2009))[11].

Next, we turn to the influence of other assets. In column three we include held-to-maturity securities, for-sale securities and trading assets (all scaled by total assets). Only trading assets turn out significant, and only at the 10% level. At this point, one has to keep in mind that non-traditional activities are likely to be negatively correlated with traditional activities (banks may specialize in either), which may create multicollinearity problems and hence affect the estimates. Therefore, in column four we use the ratio of commercial and industrial loans to total assets (C&I Loans/TA) instead of the loan-to-asset ratio (the traditional activity) as it is less correlated with the non-traditional activities. The result is that trading assets and for-sale securities in particular contribute to tail risk. Held-to-maturity securities have a positive coefficient as well, but its magnitude and significance is lower. The C&I-loans-to-asset ratio is insignificant, similar to the loan-to-asset ratio in column three.

It has often been argued that non-traditional activities contribute to (tail) risk exposure. In columns five and six, we will analyze which role financial innovations play among the non-traditional activities. First, we investigate securitization and asset sales activities. In addition to the total value of securitization and asset sales (both scaled by total assets) we also include

[10] This is in line with other studies, which identify loan growth as a main driver of risk (see, for example, Foos, Norden and Weber (2010)).

[11] Note that the interest income from loans is a part of the ROA so that potential multicollinearity issues could affect the results. However, tests in which we split the ROA into returns from loans and returns from remaining assets revealed that this is not a problem in our case.

the internal and external credit exposure arising from these activities. The internal credit exposure arises from a bank's own securitization or asset sale activities via recourse and other credit enhancing agreements between the bank and its special purpose vehicle (SPV). An external credit exposure can arise if a bank provides any kind of credit enhancements to other banks' securitization structures.

Column five shows that only the external credit exposure variable is significant and positive. This is in line with our prior findings as external credit exposure is new credit exposure taken on in addition to existing exposure. Moreover, such exposure (for example, from credit enhancements) only materializes under relatively adverse scenarios, and hence should be related to tail risk. The insignificance of a bank's own securitization and asset sale activities may indicate that opposing forces are at work. On the one hand, securitization and asset sales are, by themselves, of course a mean of off-loading risk to other market participants, making a bank less risky. In particular, if the bank keeps the equity tranche but sells senior tranches it sheds tail risk relative to normal period risk. On the other hand, recent experience has shown that these activities induced banks to take on more risk.[12] In addition, although the credit exposure seemingly disappeared from the balance sheet to the SPV (which is legally independent), the market might expect that this separation would not survive when the SPV encounters large losses. A bank might be forced to buy back the assets from the SPV to protect its reputation and customer base (as happened in the case of Bear Stearns). Therefore, the credit exposure (which is mostly tail risk exposure) may not be effectively removed through securitization.

Column six focuses on banks' derivatives activities. Based on the available data, we can make the distinction between derivatives that are held for trading purposes and derivatives that are held for other purposes (most likely hedging). A priori one would expect that the latter would reduce tail risk. The effect for derivatives trading a priori is less clear cut. Resulting counterparty risk (which tends to materialize in tail risk scenarios) may, for example, create an increase in tail risk exposure. The results in column six

[12] For example, Franke and Krahnen (2007) and Nijskens and Wagner (2008) find that securitization increases a bank's beta.

show that derivatives held for trading contribute to tail risk, while the other derivatives do not seem to affect it. The latter is somewhat surprising but may be explained by the fact that only some of these derivatives are used for hedging and that they create counterparty risk as well.

The last column takes a closer look at the importance of capital structure for tail risk. In column one we found that the leverage ratio does not contribute to tail risk exposure. We now include information on the share of deposits and the composition of deposits. In the last column of Table 1, in addition to the variables from column one, we consider the deposit-to-liabilities ratio and the ratio of time deposits above $100,000 to domestic[13] deposits. Time deposits above $100,000 are typically not insured, which makes them similar to wholesale funding, as both funding sources might be prone to runs. The results in column seven show that the leverage ratio is again not significant. Insignificance also obtains for the deposit-to-liabilities ratio. However, the time deposits above $100,000 do contribute positively and significantly to tail risk. Since these deposits are subject to withdrawal risks similar to wholesale funding, this result is consistent with Demirgüç-Kunt and Huizinga (2009) who find that wholesale funding increases bank risk[14].

3.5 Conclusion

In this paper we propose a forward-looking method to measure (systemic) tail risk exposures at banks. Tail risk is defined as a bank's exposure to a large negative market shock and it is measured by estimating a bank's share price sensitivity to changes in far out-of-the-money put options on the market, correcting for market movements themselves. Because far out-of-the-money put options on the market only pay out if the market crashes, changes in their prices reflect changes in the perceived likelihood and severity of a crash. The estimated sensitivities, in turn, represent the market's perception of exposures to a hypothetical crash, making them a truly forward-looking

[13] The FR Y-9C reports do not contain information on deposits in foreign subsidiaries, hence we scale by domestic deposits.

[14] Note that Demirgüç-Kunt and Huizinga do not distinguish between normal times risk and tail risk but focus instead on the Z-score.

measure. Another attractive feature of this measure is that it does not require the actual observation of tail risk events since it identifies banks' tail risk exposure through changes in expected market tail risk. Our measure is also relatively easy to estimate as it basically comes from an amended market regression.

The application to U.S. bank holding companies yields several interesting facts about their tail risk exposures. For example, tail risk seems to be negatively correlated with the CAPM share price beta. This suggests that banks which appear safer in normal periods are actually more crisis prone. We also find that the impact of non-traditional activities on tail risk depends on whether they leave assets on the balance sheets or not. In the former case they increase tail risk, while in the latter they do not. Our results also suggest that leverage itself does not increase tail risk, but will do so if it comes through uninsured deposits.

3.6 Tables

Table 1: Relationship between Gamma and Bank Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(TA)	-2.722***	-2.934***	-2.681***	-2.708***	-2.530***	-3.237***	-2.571***
	(0.371)	(0.384)	(0.541)	(0.492)	(0.415)	(0.476)	(0.427)
Debt/TA	0.727	36.53	-21.45	-19.68	2.117	-6.373	-3.771
	(29.25)	(30.54)	(33.01)	(30.79)	(30.08)	(29.85)	(29.97)
Loans/TA	-23.12***	-12.46***	2.485		-23.02***	-21.28***	-23.16***
	(4.433)	(4.128)	(18.17)		(4.440)	(4.637)	(4.785)
Non-Performing Loans/TL		-106.3					
		(75.26)					
Loan Loss Allowance/TL		348.2					
		(225.6)					
Loan Growth		19.10**					
		(9.178)					
Interest Loans/TL		-432.5***					
		(37.47)					
ROA		569.3***					
		(57.88)					
Held-to-Maturity Securities/TA			25.62	23.33*			
			(23.37)	(13.38)			
For-Sale Securities/TA			31.25	28.64***			
			(21.01)	(6.360)			
Trading Assets/TA			66.68*	63.06***			
			(34.97)	(20.20)			
C&I Loans/TA				-0.0419			
				(7.882)			
Total Securitization/TA					-3.396		
					(6.303)		
Loans Sold/TA					-48.42		
					(41.47)		
Int. Credit Exp. Sec.& Sales					0.953		
					(1.486)		
Ext. Credit Exp. Sec.& Sales					147.4**		
					(64.64)		
Derivatives held for trading/TA						0.361***	
						(0.108)	
Derivatives not for trading/TA						3.092	
						(3.605)	
Time Dep.>100'/Domestic Dep.							10.44**
							(4.746)
Deposits/Liabilities							3.889
							(7.265)
Observations	154242	154242	154242	154242	154242	154242	154242
R^2	0.230	0.239	0.230	0.230	0.230	0.230	0.230

This table reports the coefficients of the interaction terms between the adjusted put option and the respective balance sheet variables. It represents the effect of the respective balance sheet item on a bank's tail risk exposure where a positive value implies a larger exposure to tail risk. Robust standard errors are reported in parentheses and significance is denoted as follows: *** p<0.01, ** p<0.05, * p<0.1

3.7 Figures

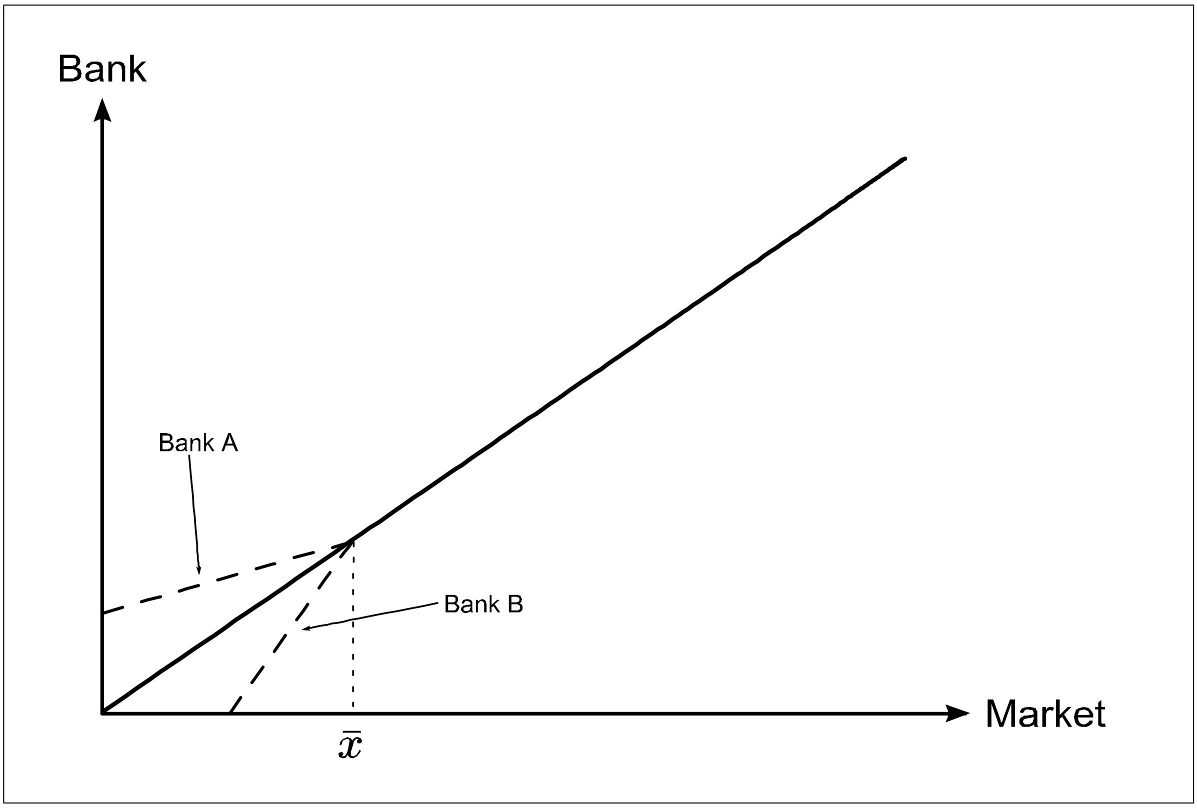

Figure 1: Relationship between Bank and Market Values

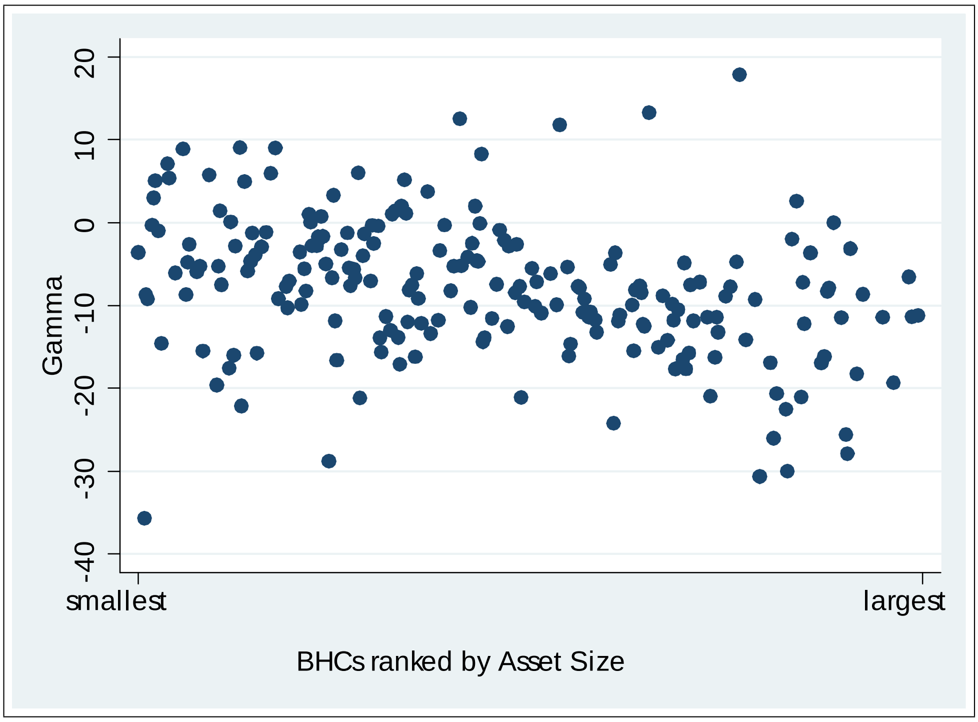

Figure 2: Tail Risk and Bank Size

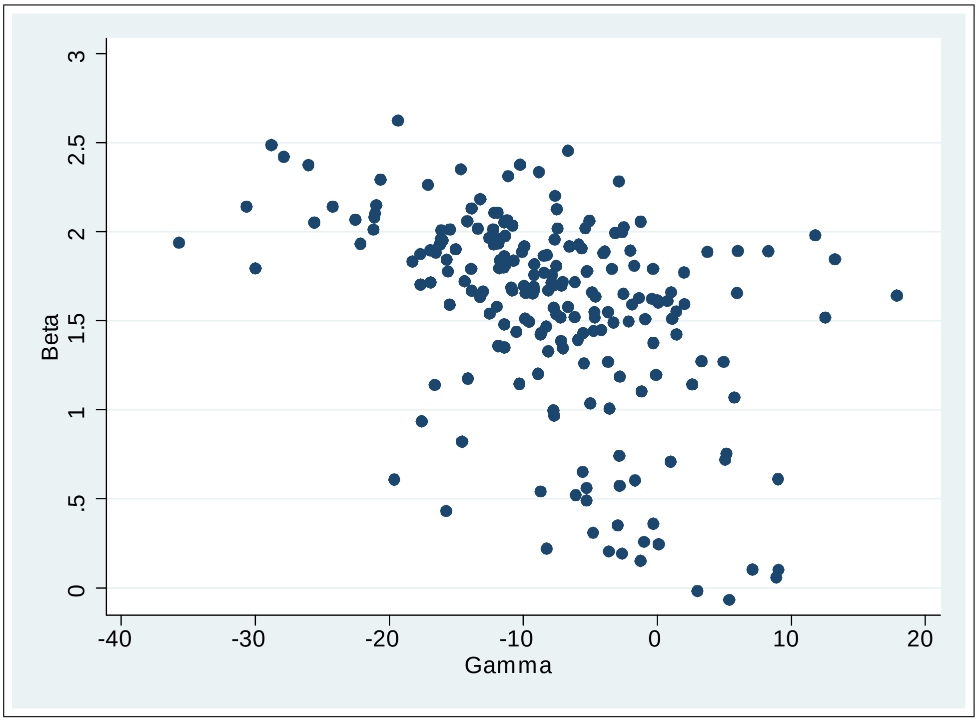

Figure 3: Gamma vs. Beta

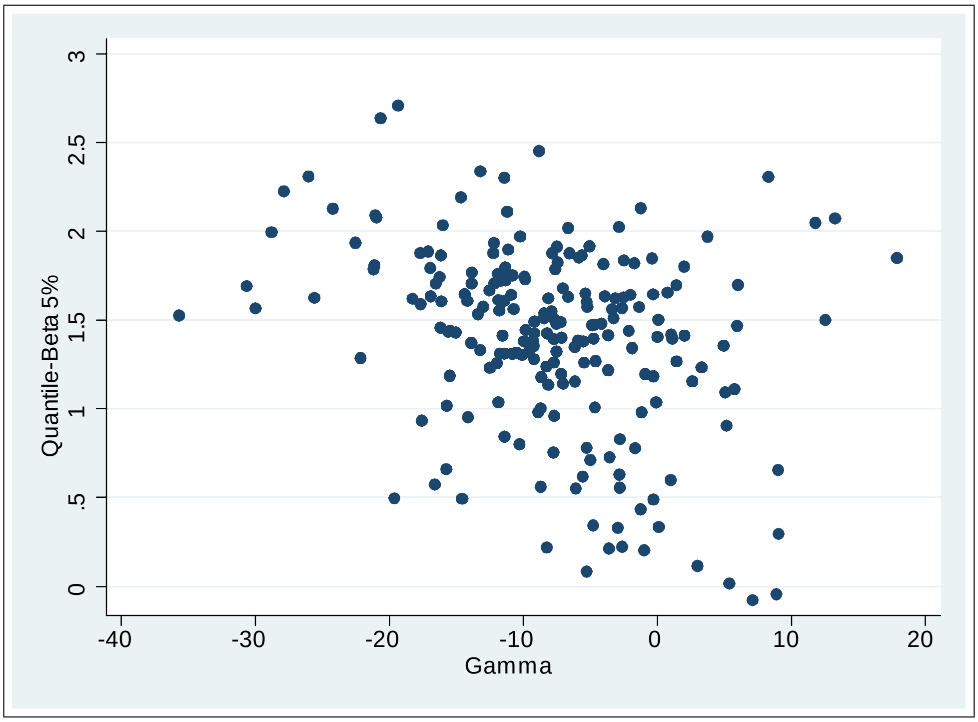

Figure 4a: Gamma vs. Quantile-Beta (5% Quantile)

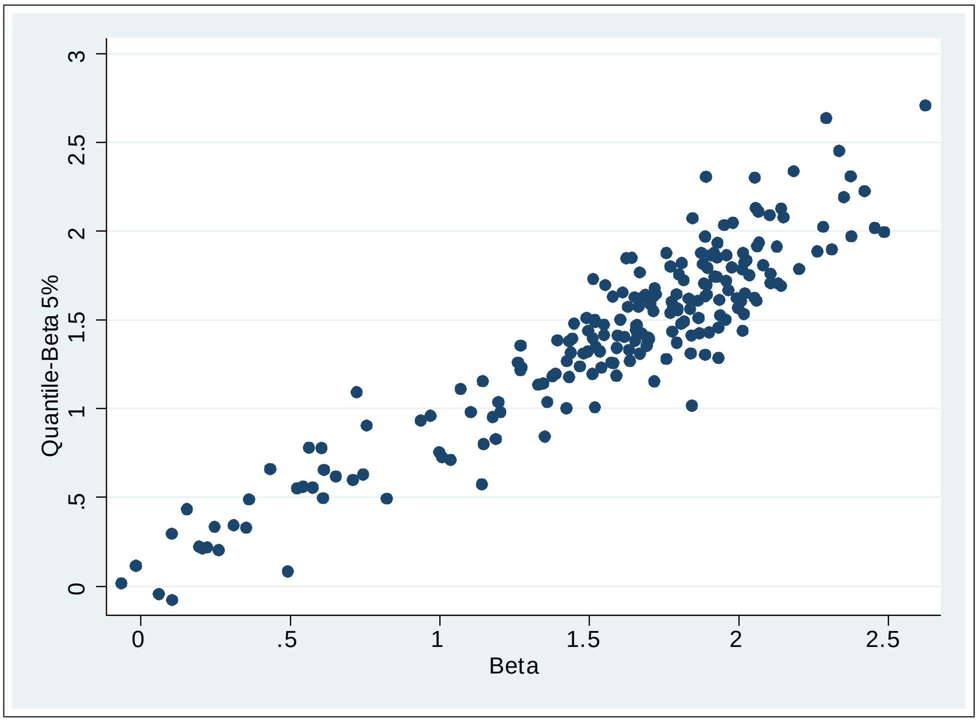

Figure 4b: Beta vs. Quantile-Beta (5% Quantile)

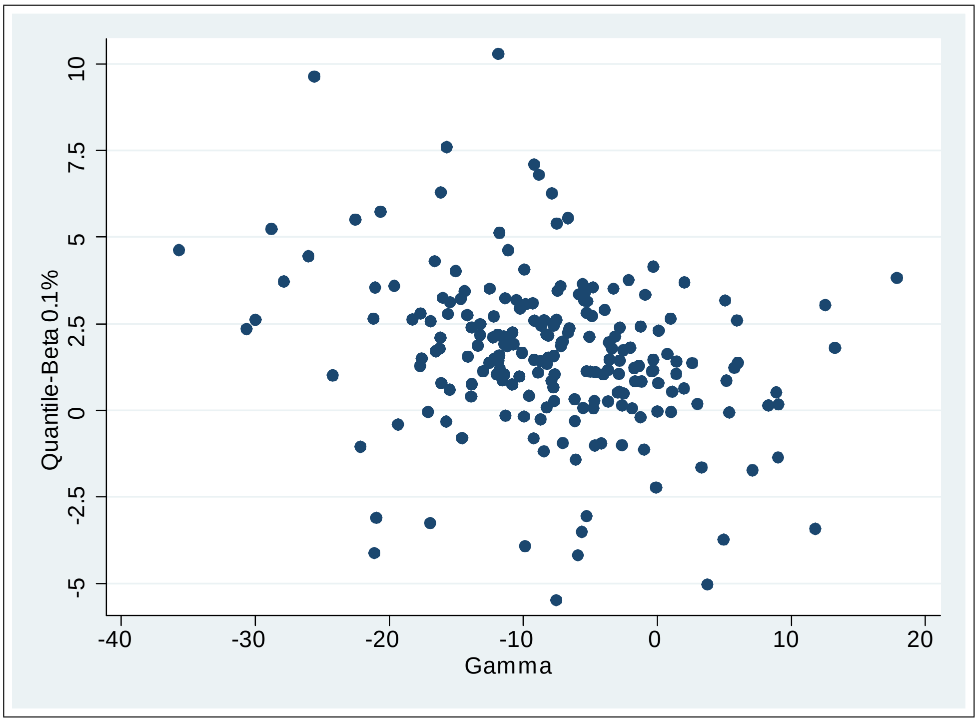

Figure 5a: Gamma vs. Quantile-Beta (0.1% Quantile)

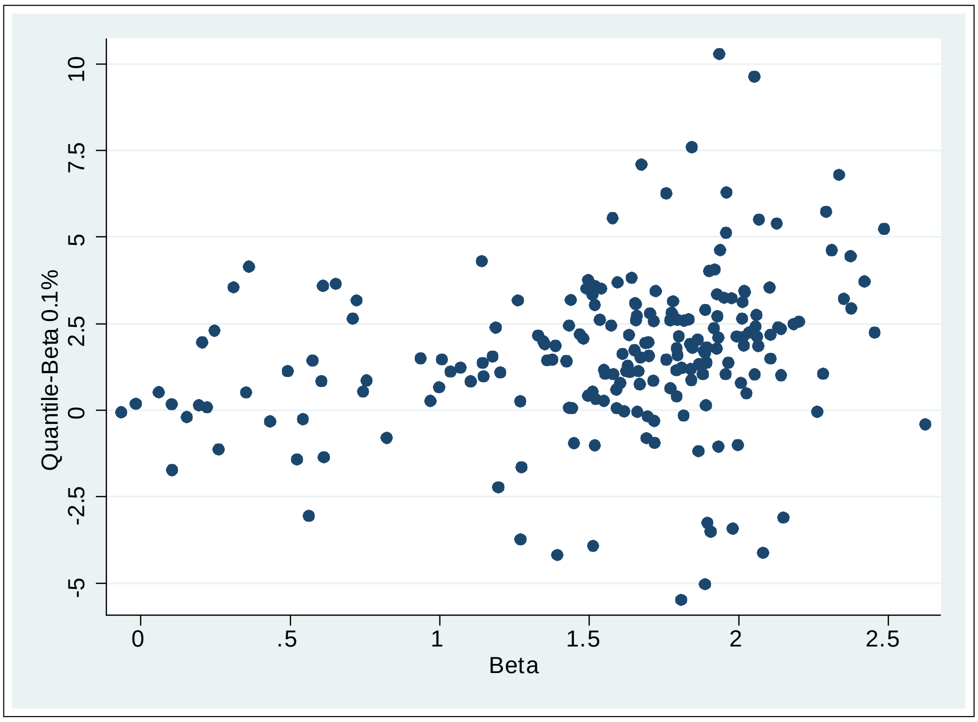

Figure 5b: Beta vs. Quantile-Beta (0.1% Quantile)

Chapter 4

Bank Aggressiveness in the Syndicated Loan Market

4.1 Introduction

In perfectly competitive loan markets without any frictions loan spreads should represent the borrower's underlying risks and thus be mainly determined by borrower and loan characteristics. In reality, however, credit markets exhibit various deviations from such an outcome. Depending on the severity of these frictions loan spreads can exhibit larger or smaller deviations from this efficient pricing rule that is based on the borrower and loan characteristics. The most important frictions include asymmetric information, imperfect competition, and legal constraints. As a result of these frictions banks screen and monitor borrowers and may gain bargaining or market power vis-à-vis borrowers. In short, bank supply conditions and bargaining considerations matter.

This paper studies the part of the loan pricing that is not related to borrower and loan characteristics. I regress the loan spread of a syndicated loan on borrower and loan characteristics. The residual of this pricing regression is averaged over all borrowers at the bank level and is called pricing aggressiveness. It represents the part of the loan spread that cannot be explained by borrower or loan characteristics but instead by a bank's characteristics[1].

[1]In principle it is possible that unobserved borrower characteristics may also play a

Factors that influence these characteristics include, for example, bank credit supply conditions, the general bank strategy, and its risk appetite. This implies that aggressiveness may differ from a bank's riskiness, which is often used as a key variable in the regulatory and supervisory process. A bank with a growing risk appetite, for instance, may decide to focus lending more on riskier borrowers. Aggressiveness, on the other hand, may change even when the risk characteristics of the loan portfolio remain the same. It thus represents a different dimension of bank behavior[2]. Given that changes in aggressiveness may have implications for the soundness of a bank, a proper understanding of banks' aggressiveness should be in the interest of supervisors and regulators.

To my knowledge, this is the first paper that attempts to investigate the aggressiveness of banks via the pricing channel. The existing literature often focuses on loan growth or covenants in loans to proxy for aggressive or risky bank behavior (see, for example, Mason et al. (2009) and Foos, Norden and Weber (2010)). The advantage of the pricing approach is that changes in a bank's loan policy can be detected more timely and at a more detailed level compared to the balance sheet information. This may give supervisors and regulators early indications of changes in bank behavior well before these changes can be detected in the balance sheet. These early indications may be particularly valuable in times of crisis since balance sheet information has been shown to be less reliable especially in those times as, for example, Huizinga and Laeven (2009) have shown.

The proposed aggressiveness measure is studied in the context of the global syndicated loan market. Using data from the Reuters LPC Dealscan database, I obtain detailed information on 40203 syndicated loans from around the world for the years 1987 to 2009. I focus on the top 100 lead ar-

role. For example, for all given observable characteristics a borrower may be more or less risky. In this paper it is less of a concern since I aggregate the estimated residuals at the bank level so that idiosyncratic unobservable risks should cancel out.

[2] I prefer the term aggressiveness over the term discretion since it already gives the reader an idea of the direction of discretion. A very aggressive bank uses its discretion to underprice a loan for the given borrower and loan characteristics while a bank with very little aggressivenss uses the discretion to overcharge a borrower for the given borrower and loan characteristics. In both cases discretion is involved but only the term aggressiveness clearly shows which type of discretion a bank is exhibiting.

rangers, defined as the banks with the 100 largest number of deals arranged during the sample period. I estimate the aggressiveness measure and examine it across various dimensions.

I find that the average aggressiveness varies considerably among the banks. Even among selected top 10 lead arrangers a difference of 50 basis points can be observed for most years of the sample. Similarly, the difference between the ten most and ten least aggressive lead arrangers is at least 150 basis points throughout the sample. However, the aggressiveness differences are larger in the first part of the sample. They tend to converge somewhat around the year 1999 before they widen slightly in the following years and increase substantially in the last years of the sample. A similar observation can be made for the full sample including all top 100 lead arrangers. This time series variation does not seem to be related to business cycle movements, as measured by U.S. GDP growth. They only seem to influence the aggressiveness in the last years of the sample where the financial crisis hit the global economy. Instead, other factors such as, for instance, idiosyncratic pricing seem to be related to aggressiveness.

Overall, the analysis of the top 10 lead arrangers, all lead arrangers, and the most and least aggressive lead arrangers presents one consistent picture. Throughout the sample there is considerable variation of aggressiveness over time and among banks. Especially the variation among banks suggest that seemly identical borrowers can face different loan spreads depending on the aggressiveness of the bank. These differences can be as large as 50 basis points even among the top 10 lead arrangers. This implies a certain degree of inefficiency as identical borrowers should face identical loan spreads. Instead the results suggest that borrowers can pay too much or too little for their loans, which may result in an inefficient allocation of capital at the aggregate level and thus lower economic growth.

The differences in aggressiveness among banks warrant a closer look into bank-specific factors that may help to explain these differences. In order to understand how bank-specific factors may influence a bank's aggressiveness, I obtain bank-specific balance sheet information from the Bankscope database and regress the average yearly aggressiveness per bank upon lagged yearly bank characteristics. I find that loan loss provisions are significantly related to aggressiveness, both alone and in combination with loan loss reserves or nonperforming loans. Higher provisions the year before suggest a less aggressive behavior in the current year. This result suggests that when problems in the loan book arise, banks do not just reduce quantity but also adjust the pricing. In addition, I find that an increase in bank size is related with lower aggressiveness while banks with a high leverage ratio seem to price more aggressively. The latter result is likely due to a high overall risk appetite. Loan levels and loan growth, on the other hand, do not seem to influence the aggressiveness. Similarly, the liabilities structure does not seem to influence a bank's aggressiveness either.

The last question that I address is the question whether the aggressiveness can indicate future changes in a bank's condition. This application may be of particular value in, for example, supervisory and regulatory processes as they often rely on bank-specific balance sheet information, which are typically reported with a lag. I find that less pricing aggressiveness is related to increasing return on assets in the short run (one year) and lower loan loss reserves and a higher Tier one capital ratio over the short and medium term (one to three years). Taken together, these findings may be of interest for a supervisor or regulator as they suggest that a bank's aggressiveness can be used as an leading indicator for coming changes in a bank's balance sheet items and thus provide more timely updates about the condition of a bank.

The paper proceeds as follows. Section 2 describes the process of loan syndication and Section 3 reviews the literature. Section 4 explains how the pricing aggressiveness is measured, including a brief discussion of its major properties. The data and the empirical results are presented in Section 5 and 6, respectively. Section 7 concludes.

4.2 Syndicated Loans

In a syndicated loan, a collection of banks forms a bank syndicate in order to jointly make a loan to a borrower[3]. That loan can be made in one whole sum or split up into several tranches (also called facilities) with varying sizes spreads, maturities and other characteristics The banks in the syndicate can be divided into two groups, namely lead arrangers and participant banks. The lead arrangers can be seen as the senior members of the syndicate as they establish and maintain a relationship with the borrower. This implies that they directly negotiate with the borrowing firm but are also responsible for the information collection and distribution among the syndicate. In addition, they are expected to hold a larger portion of the loan than other participating banks. Once the loan is made they are also responsible for the monitoring and administration of the loan. Note, that depending on the preferences of the borrower, there can be one or several lead arrangers in the syndicate. In the latter case, the responsibilities among the lead arrangers may also differ, as Sufi (2007) and François and Missonier-Piera (2007) note.

Despite these responsibilities lead arrangers may have good reasons to act as a lead arranger. First, it enables a bank to cultivate the relationship with the borrower while diversifying its loan exposure and income. This can be achieved because the lead arranger is able to meet the borrower's demand for a loan without risking excessive single-name exposures, which ensures that regulatory limits on risk concentration are adhered to. The income is diversified because the lead arranger not only earns the spread on the loan but also some fees for arranging and administering the loan. Moreover, being selected as a lead arranger is seen as good advertisement since it is a prestigious position and banks are keen on publishing this information through the league tables, as Ivashina (2009) notes.

Participant banks form the junior group of the syndicate. The size and composition of the group typically depends on the size, complexity and pricing of the loan. In addition, it may be restricted by the willingness of the borrower to increase the range of its banking relationships as Gadanecz

[3]The information in this section is based on Gadanecz (2004) and Sufi (2007). For more information on syndicated loans, see also Esty (2001).

(2004) notes. The junior members are typically not involved in the loan negotiations nor do they receive any fees. Instead they are approached by the lead arrangers and simply asked whether they want to join at the negotiated conditions, that is to provide the required capital and receive the margin that the lead arranger negotiated with the borrower. Nevertheless, these banks may have several reasons for participating in the syndicate. It may be out of necessity if the banks simply lacks the origination capability in certain types of transactions, geographical areas or industrial sectors. However, according to Gadanecz (2004) it may also be a deliberate choice if the bank wants to cut down on origination costs. In addition, participating banks may also hope for additional business in the future, such as treasury management, corporate finance or advisory work[4].

According to Sufi (2007) the process of a loan syndication works as follows. The borrowing firm and the lead arrangers negotiate a preliminary loan agreement ("mandate"), which specifies the loan amount, a range for the interest rate, covenants, fees, and collateral. After signing this agreement, the lead arrangers approach potential participant lenders for the funding of the loan and provide them with an information memorandum, which contains detailed and confidential information about the borrowing firm. After all participants agreed to fund part of the loan, the loan agreement is signed by all parties. Except for the share of the loan the contract terms are typically identical for all syndicate members, which implies that only one contract exists. Each member is responsible for providing her share of the loan. The lead arranger, in turn, also has monitor the firm, govern the terms of the loan, administer the drawdown of funds, calculate interest payments, and enforce financial covenants because she is typically also chosen to be the "agent" bank. For arranging and managing the syndicated loan the lead arranger receives various fees, which is paid by the borrowing firm. In addition, the borrowing firm also has to pay fees to the banks for providing the capital (both in drawn and undrawn states)[5]. The so-called "All-in spread drawn" is often reported as a measure of the annual borrowing costs for the borrower.

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[4] Gadanecz (2004) quotes Allen (1990) as the source but I was not able to confirm this directly as I could not find Allen (1990) on the internet.

[5] For a more detailed discussion of the fees, see Gadanecz (2004).

It is expressed in basis points paid over LIBOR and includes various fees and the arranged spread. According to Ivashina (2009), it is defined by DealScan as the total annual cost paid over LIBOR for each dollar used under the loan commitment.

4.3 Literature

The theoretical literature on the motives for financial institutions to form a syndicate typically focuses on securities syndicates in general rather the loan syndicates in particular. A non-exhaustive list of motives includes risk diversification and risk sharing (Wilson (1968), Mandelker and Raviv (1977), and Chowdhry and Nanda (1996)), the exchange of information, experience, and expertise (Millon and Thakor (1985), Sah and Stiglitz (1986), Tykvová (2007), and Biais and Perotti (2008)), solving moral hazard in team problems (Pichler and Wilhelm (2001, and Bubna (2002)), preventing competition (Casamatta and Haritchabalet (2007)), deterrence of theft of idea (Bachman and Schindele (2006)), and inducing information revelation of the syndicate members (Cestone et al. (2007)).

On the empirical side, various strands of the loan syndication literature have been explored. Among the motives for loan syndication, diversification and capital regulations seems to be the main reasons (Simons (1993) and Dennis and Mullineaux (2000)). When investigating what types of loans are more likely to be syndicated, Simons (1993) uses ex post examiner ratings as a proxy for quality and finds that lead arrangers syndicate a larger portion of quality loans. Dennis and Mullineaux (2000) find that lead arrangers are more likely to syndicate loans when the lead arranger has a good reputation, when the borrowing firm is public and thus more information about the firm is available, and when the loan's maturity increases.

The pricing strand of the empirical side is explored a bit more in detail. Examples include Angbazo et al. (1998), Thomas and Wang (2004), Harjoto et al. (2006), and Ivashina (2009)[6]. The analysis Angbazo et al. (1998) examines the determinants of the credit spreads on highly leveraged transaction

[6]Note that in this section I only present the main findings of the pricing papers. More detailed information about the specific variables can be found in section 4.4.

(HLT) loans. In addition, it analyzes how well the HLT loan market and the competing corporate bond market are integrated. Their findings suggest that the pricing in the HLT loan and corporate bond markets diverge. Moreover, they find that several borrower quality characteristics to be important determinants of HLT loan spreads. These will be explained in section 4.4 more in detail. Similarly, Thomas and Wang (2004) examine the integration of syndicated loan and junk bond markets and find that market integration has dramatically increased since traded HLT syndicated loans were available as an alternative to other high-yield bonds. Harjoto et al. (2006) compare the syndicated loan pricing of investment and commercial banks. They find that investment banks seem to charge less for credit risk on the margin but that this difference is much weaker once borrower specific information is included. Ivashina (2009) addresses the question how large the impact of asymmetric information between the lead arranger and members of the syndicate on the loan spread is. In theory there are two opposing forces. On the one hand, syndicate members require a premium for the informational advantage that the lead arranger has. Alternatively, they ask him to retain a larger share of the loan. The lead arranger, on the other hand, demands a diversification premium if he has to hold a relatively large share. Faced with this problem of endogeneity of the spread and the lead's share Ivashina (2009) is able to identify the asymmetric information effect using the idiosyncratic credit risk of the lead bank's loan portfolio as an instrument.

Apart from the pure pricing issues, other deal characteristics have also been explored. Covenants are more likely to be used when the borrowing firm is small, has high growth opportunities, or is highly leveraged (Bradley and Roberts (2004)) while restrictions on loan sales are more likely to be imposed when the borrowing firm is small (Pyles and Mullineax (2008)).

One of the larger strands of the literature investigates the structure of the syndicate. Melnik and Plaut (1996) investigate underwriting syndicates in the Eurocredit market. Their evidence suggests that lead managers are primarily recruited for risk bearing and sharing purposes. Regular managers, on the other hand, seem to be primarily recruited to expand the distribution of the loan. Song's (2004) findings suggest that members of the syndicate as well as the borrower benefit when underwriters with complementary abilities form a syndicate. François and Missonier-Piera (2007) find that lead arrangers share administrative tasks with so called co-agents when the loan size is small and its maturity is short. However, once the informational asymmetry between the lead arranger and other syndicate members becomes larger, co-agents also act as delegated monitors. This is because they gain insight through the administrative tasks and are thus better able to monitor the lead arranger. In addition, Sufi (2007) finds that lead arrangers chose participants that are more likely to "know" the firm when there is limited information about a borrower. Cai et al. (2010) investigate how the similarity of banks in terms of lending expertise affect the organizational structure of a syndicate. The authors measure the similarity by a set of Euclidean distances between two lenders across various dimensions and find that lead arrangers prefer banks with a small distance, hence a similar lending expertise. These close competitors obtain more senior roles and hold larger loan shares. The authors suggest that this is done to delegate some monitoring responsibilities and thus lower the overall loan syndication costs.

Information asymmetries within the syndicate also play a major role in shaping the structure of the syndicate. When the lead arranger has better or private information about a borrower, other syndicate members may, in theory, require him to hold a larger portion of the loan in order to keep up his incentives to properly screen and monitor the loan. Various papers confirm this theoretical reasoning. Dennis and Mullineaux (2000) proxy the quality of the information about the borrower with credit ratings and stock exchange listings and find evidence that better quality enables lead arrangers to keep a smaller share of the loan. With similar proxies, Lee and Mullineaux (2004) find that syndicates are more concentrated when the information about a borrowing firm is scarce and when the borrower's credit risk is larger. Jones, Lang, and Nigro (2005) proxy information asymmetry with dummies for the availability of a CUSIP number, the existence of a branch in the state of the borrower's headquarter, and the borrower being active in the service sector. All proxies suggest that greater information asymmetry is associated with a larger loan share. In addition, the authors find that the retained loan share is larger if the lead arrangers are less capital-constrained, their loan portfolio has a lower concentration of lower quality loans, and the maturity is longer since longer maturities are typically granted to better quality borrowers. Sufi (2007) uses proxies similar to Dennis and Mullineaux (2000) and Lee and Mullineaux (2004) and concludes that higher degrees of information asymmetries force lead arrangers to retain a larger share of a loan and thus form more concentrated syndicates.

There exist, however, also mitigating factors that partly offset the effects of the information asymmetries. The reputation of the lead arranger seems to be a prominent one. Dennis and Mullineaux (2000) measure reputation with the lead arranger's credit rating and the volume of repeat business between the lead arranger and a syndicate member and find that a lead arranger's reputation can mitigate the effects of asymmetric information. Similarly, Sufi (2007) takes the lead arranger's last year market share (based on amounts) as a proxy for reputation and also finds that reputation can reduce, but not eliminate, problems of information asymmetry. He also suggests that borrower reputation, measured by the repeated access to the syndicated loan market, can have a similar effect. Lastly, De Haas and van Horen (2010) investigate how macroeconomic factors influence the syndicate structure. In particular, they investigate how the recent financial crisis affected the screening and monitoring efforts and thus the syndicate structure. Their evidence suggests that during the crisis syndicates became significantly more concentrated, which, according to the authors, points to an increased focus on screening and monitoring. Ivashina and Scharfstein (2010a), on the other hand, investigate how the recent financial crisis affected the supply of syndicated loans. They find that especially those banks had to cut lending that did not have easy access to deposit financing and those that co-signed credit lines with Lehman Brothers and were thus forced to provide more liquidity.

Legal and financial systems can also influence the syndicate structure. Esty and Megginson (2003) take the La Porta et al. (1998) creditor rights index to investigate if creditor protection and the enforcement of laws have an impact on syndicate structure. They find that in order to facilitate monitoring and low cost contracting, smaller and more concentrated syndicates are formed whenever strong creditor rights and reliable legal enforcement exist. However, in the absence of strong creditor rights and reliable legal enforcement, lenders prefer to form larger and more diffuse syndicates in order to discourage strategic default. Similarly, Esty (2004) examines under which circumstances foreign banks are more willing to provide funds. His evidence suggests that this is more likely in countries with a better legal enforcement and better creditor rights, and in countries with less developed financial systems and lower shares of government ownership of banking assets. Qian and Strahan (2007) also follow La Porta et al. (1998) and they, too, find that increased participation by foreign banks is more likely with a strong protection of creditor rights. Moreover, they find that the latter is also associated with greater concentration of loan ownership and longer maturities.

Another strand of the literature uses event study methodologies to examine the announcement effects of syndicated loans. Megginson, Poulsen, and Sinkey (1995) examine the overall announcement effect of syndicated loans on the stock return of the participating banks. Compared to sovereign loans, corporate loans in the 1980's are associated with significant abnormal positive returns. Among the corporate loans alone, loans with a takeover financing purpose result in significant positive returns. The authors interpret this as banks being able to earn larger returns if the borrower is in urgent need of large amounts of capital to finance takeovers. Preece and Mullineaux (1996), on the other hand, focus on the effect on the borrower's stock return by investigating whether the size of a lending syndicate has an effect on the borrower's stock return. Their analysis is based upon the hypothesis that larger syndicates make negotiations about loan restructuring more difficult due to potential hold-up problems. Hence, larger syndicates should result in lower returns if contractual flexibility is a source of value to borrowers. The evidence supports their hypothesis since the relationship between abnormal returns and syndicate size is negative.

In addition to investigating deal characteristics at the time of the syndication the default performance of syndicated loans can also be examined. Altman and Suggitt (2000), for example, find almost no difference in the cumulative default rates of syndicated loans and comparably rated corporate bonds when focusing on the four and five year maturity horizon. Syndicated loan default rates, however, seem to be higher in the first two years after issuance. As noted above, Cai et al. (2010) examine the similarity in lending expertise among syndicate members and their effect on various outcomes.

With respect to borrower default performance, they find that borrowers are actually somewhat more likely to default if syndicate members have a similar lending expertise.

Finally, Ivashina and Scharfstein (2010b) examine whether syndicated loans also have an effect on macroeconomic variables. More precisely, they investigate whether loan syndication can amplify credit cycles. The hypothesis crucially depends on whether in a recession the lead arrangers have to retain a larger or smaller share of the loans. Should banks be forced to retain larger shares of the loans on their books capital constrained banks might be less willing to participate in further syndications, which might amplify credit cycles and vice versa. Their evidence suggests that the lead arranger's share increases during recessions, which has the potential to amplify credit cycles.

4.4 Measuring Aggressiveness in the Syndicated Loan Market

In a first-best world without any market frictions loan spreads should be fully determined by observable information. In reality, however, credit markets, like many other markets, exhibit various deviations from the first-best outcome. The most important examples include asymmetric information, legal constraints, and imperfect competition. Depending on the severity of these frictions loan spreads can exhibit larger or smaller deviations from the first-best pricing rule. This dispersion may be explained by screening and monitoring efforts of banks, but also market power of banks or bargaining power of banks and borrowers. Especially the latter two imply that banks have some room for maneuver and are thus able to actively chose the loan spread for given observable borrower and loan characteristics. This willingness to make a loan is exactly what I am after. Correcting for borrower, loan and loan market characteristics, loan spreads still differ due to a varying bank willingness to make a certain loan.

I call this aggressiveness for the following reasons. First, imagine that a loan exhibits a spread much larger than its observable characteristics would justify. In this case I would speak of a low willingness to make that loan since the bank asked for a high spread. However, this case could be confused with a large reluctance to make that loan so that one might ask why the bank made the loan in the first place. To avoid this confusion I prefer to speak of pricing aggressiveness or simply aggressiveness. Second, willingness to make a loan might be confused with risk appetite. One could argue that whenever a bank has a larger risk appetite it also more willing to make a loan. However, my measure of aggressiveness differs from risk appetite as I will discuss more in detail in section 4.4.1.

The general approach to measure aggressiveness is as follows. First I regress the all-in spread of a syndicated loan on borrower, loan and loan market characteristics. This is done to control for all potential borrower influences like, for example, its risk characteristics, a proxy for the information asymmetry between borrower and lender, and the bargaining power of the borrower. Similarly, I want to control for all loan characteristics and the lead arranger's position in the loan market. The latter is done to rule out that aggressiveness depends on the market position of the lead arranger because in that case I would probably find that banks with a larger market share are automatically less aggressive.

The resulting residual of that regression is the part that cannot be explained by those observable characteristics. This is what I define as a bank's aggressiveness, as it represents the part that depends on a bank's willingness to make that particular loan, given the existing risk characteristics.

More precisely, the all-in spread of a syndicated loan i is regressed upon available borrower characteristics W, loan characteristics X and lead arranger characteristics Z, as shown in equation (4.1):

$$allinspread_i = \alpha + \beta W_i + \gamma X_i + \delta Z_i + \varepsilon_i \tag{4.1}$$

Next, the residual ε_i is taken as the lead arranger's aggressiveness in the syndicated loan i[7]. In case the syndicated loan contains several tranches, the analysis is done at the tranche level rather than the deal level, as the tranches

[7] Note, that in the following analysis the residual is not analyzed at the individual loan level but is averaged across various dimensions, such as, for example, the bank-year level. Estimating the residual at the individual loan level still has the advantage that the dispersion can be analyzed, too.

are likely to have different spreads, amounts and maturities. However, in cases of several tranches, I cannot use all tranches of the deal and thus focus on the largest tranche of each deal. The reason is that I cannot treat each tranche as an independent observation as I discuss more in detail in the data section.

Note, that syndicate characteristics like, for instance, the number of lead arrangers and their share of the loan (among each other and compared to the participants), are not included as explanatory variables. This is because the spreads of a syndicated loan and the syndicate characteristics are determined simultaneously, as Sufi (2007) and Ivashina (2009) discuss more in detail. To prevent the resulting issues of endogeneity, I decided to leave these characteristics out.

The borrower characteristics W include the following variables. *Sales*, measured as the natural logarithm of the company sales, is a proxy for information asymmetry. According to Harjoto et al. (2006), a larger company with higher sales is associated with lower information asymmetries so that the expected coefficient should be negative. Based on the same reasoning, the coefficient for *Ticker*, a dummy equal to one if the borrowing company has a ticker symbol, should be negative, too. Another set of borrower characteristics are *Credit Ratings* (see, for instance, Ivashina (2009) and Sufi (2007)). They represent a set of dummies (one for each Standard & Poor's senior debt rating) with BBB being the omitted category. In general it is expected that spreads increase with a deteriorating credit rating. In addition, I employ the dummy *Not Rated*, which is equal to one if a borrower is not rated and the dummy *CP Rating*, which is equal to one if the borrower has a commercial paper rating. The expected coefficient of the former dummy is positive as it is a proxy for larger information asymmetries while the expected coefficient of the latter is negative since a commercial paper rating is an additional signal that reduces the informational asymmetry. *Previous Relationship* is a dummy that is equal to one if over last 3 years the same lead arranger arranged a loan for same borrower (Ivasina (2009)) while *Borrower Reputation* represents the number of syndicated loans that the borrower obtained before (Sufi (2007)). The expected signs of both dummies should be negative since in both cases the borrower is better known to the market and the lead arranger. The last two sets of borrower characteristics include industry and country dummies. The industry dummies are at the two digit SIC level with no information about the SIC code being the omitted category. The USA forms the omitted category of the country dummies.

Among the loan characteristics X, *Secured* represents a dummy equal to one if the loan is secured. In theory, the sign of its coefficient is ambiguous, because on the one hand pledging collateral makes the loan safer but on the other hand banks will require collateral for borrowers with higher risk. Harjoto et al.(2006), however, expect a positive sign as they note that prior studies, such as Angbazo et al. (1998), mostly find higher spreads for secured commercial loans. This is because lenders often require collateral on high-risk loans but the pledged collateral cannot fully offset the initially higher spread. A similar theoretical reasoning applies to the dummies *Financial Covenants* and *Performance Pricing*, which are equal to one if the loan contract includes financial covenants and performance pricing, respectively. Ivashina (2009) notes that both measures itself help to reduce moral hazard issues resulting from asymmetric information, making the loan less risky. However, it is likely that both measures are only taken when the borrower is very opaque and risky. Consequently, the expected coefficients are ambiguous. The last two proxies for informational asymmetry are the natural logarithm of the tranche amount, *Amount,* and the *Number of Facilities* (see, for instance, Ivashina (2009)). The expected sign of both is ambiguous. On the one hand, a larger amount or a larger number of facilities makes the overall deal bigger and that is typically associated with larger, less opaque borrowers. On the other hand, it typically raises the amount each lead arranger has to keep, which increases its risk concentration and in turn raises the spread.

In order to control for the maturity of a loan I follow Harjoto et al.(2006) by using three dummies. *Short Maturity* is a dummy equal to one if the loan is a revolver and has a maturity of less than 365 days. According to the authors, its coefficient should be negative because these loans should be cheaper as they do not require any regulatory capital. *Intermed Maturity* is equal to one if the maturity of the loan ranges from two to five years and *Long Maturity* is equal to one if the maturity exceeds 5 years. The expected coefficients of the latter two dummies are ambiguous as Harjoto et al.(2006) point out. They present various papers with mixed evidence on the relationship between spreads and maturity.

Other loan characteristics that need to be controlled for include a term loan indicator and the purpose of the loan, as, for example, Angbazo et al. (1998) point out. They find that, ceteris paribus, term loans have higher spreads than revolvers and that the spread can differ depending on the purpose of the loan. Therefore, I include the dummy *Term*, which is equal to one if the deal contains a term loan, and, following Sufi (2007), 4 *Loan Purpose* dummies for general corporate purposes,debt repayment, acquisitions, and backup lines, respectively. All other purposes form the omitted category. The expected signs of the coefficients vary by the purpose while the expected sign for *Term* is positive.

The last group of explanatory variables includes the lead arranger characteristics Z. Ivashina (2009) calculates the lead arranger's ranking based on its market share using the number of deals. The idea behind the market share is that lead arrangers in general are forced to retain a larger share of the loan when the borrower is more opaque. In that case more intense screening and monitoring is required so that participants may only be willing to buy a share of the loan if the lead arranger has enough own money at stake to ensure that she is fulfilling her duties diligently. However, this effect may be less pronounced when the lead arranger has a more established reputation and may therefore result in lower spreads for these lead arrangers. Consequently, the expected sign for *Lead Ranking* is positive, given that the largest lead arranger is ranked number one, the second largest is ranked number two and so forth. One drawback of this ranking is that the distance between two neighboring arrangers is always the same (namely one rank) while in reality the distance between them (in terms of market share) may differ. Another problem is that the ranking may not be informative if several banks did not arrange a deal in the year before. Therefore, I also employ Sufi's (2007) specification, in which he calculates the market share based on the overall amount a lead bank arranged in the previous year. Based on the previous reasoning, the expected sign for *Lead Reputation* is negative. A summary of the variable description is also presented in Table 1.

4.4.1 A Brief Discussion of the Aggressiveness Measure

Before I turn to the empirical results, a brief discussion of the aggressiveness measure is in order. In principle, this measure can be applied to any bank as long as it can be assured that the bank has active control over the pricing of the loan. In the context of the syndicated loan market, this seems to be the case only for the lead arranger banks, since they can actively negotiate the terms of the deal. Participant banks on the other hand only have the choice whether to participate or not and quite often they feel pressured to do so in order to prevent damages to the relationship with the borrower. Therefore, in this paper I apply this methodology only to lead arranger banks. Outside the syndicated loan market, this methodology could in principle be applied whenever detailed data on the loans are available.

Aggressiveness is defined as the residual of a regression of the all-in spread on borrower and loan characteristics. It represents the part of the loan spread that cannot be explained by borrower or loan characteristics but instead by a bank's characteristics and behavior. Examples include, for example, bank credit supply conditions, the general bank strategy, and its risk appetite. In principle it is possible that aggressiveness is also related to unobserved borrower characteristics. For example, for all given observable characteristics a borrower may be more or less risky. In this paper it is less of a concern since I aggregate the estimated residuals at the bank level so that idiosyncratic unobservable risks should cancel out. One might still object that it is also possible that there is a systematic shift in risk if, for example, a whole industry becomes riskier. I at least partially control for this by including industry and country dummies in the estimation of the residual. The potential remainder is simply included in the residual although it may not represent an active choice variable of a bank.

Although aggressiveness may include a bank's risk appetite, it should, in general, differ from a bank's riskiness, which is often used as a key variable in the regulatory and supervisory process. For example, a bank with a growing risk appetite may decide to lend more to lower rated companies or at longer maturities. Bank aggressiveness, however, does not need to change in that case. Alternatively, a bank's aggressiveness may change even when the risk characteristics of the loan portfolio remain the same. It is therefore a different dimension of bank behavior. This dimension may be relevant to regulators and supervisors since a change in aggressiveness could result in changes in profitability even when the risk profile remains unchanged. Changes in profitability, in turn, can affect the overall soundness of the banking system and thus have real economic consequences as the latest financial crisis has recently shown.

This also highlights the need to examine potential differences in aggressiveness among banks and over time, and to understand the potential determinants of these differences at the bank level. Therefore, only borrower, loan, and loan market (more precisely, the lead arranger's position in the market) information are included in the estimation of the aggressiveness measure. This allows me to examine the residual over time and across banks. In order to understand the potential determinants of aggressiveness at the bank level, bank specific information is introduced in section 4.6.3. This two step approach (first estimating the aggressiveness measure and then relating it to bank specific information) implies that the results are biased against finding significance of bank specific information. It thus makes significant results more credible, which is important when supervisors and regulators want to use this information. Moreover, the two step procedure allows me to first estimate the aggressiveness and then check if it is related to future changes in bank characteristics, hence acting as a leading indicator without interpreting the results in a causal way. This might not be possible in the one step setting where I would control for balance sheet characteristics already in the estimation of the aggressiveness measure.

Another argument in favor of the two step method is that it ensures consistency in the methodology across all explored dimensions including the investigation of loans with more than one lead arranger, which is something that has not been done in this paper but may be the subject of future research. When using the one step method on loans with, for example, two lead arrangers the following problem arises. Once you want to include bank specific characteristics you either need to somehow average the characteristics from both banks or you need to double the observation in order to include the variables for each bank once. In the former case the method of averaging may influence the results or the whole exercise of averaging may not yield reasonable figures. In the latter case, you have to increase the number of observations (double in the case of two lead arrangers, triple for three lead arrangers and so forth) although they are not independent of each other, which may make statistical inferences problematic.

Note, that aggressiveness could be related to loan volume as less aggressiveness may be related to negative loan growth. However, a situation could also exist in which overall loan volume is constant (due to, for instance, relationship commitments) but a bank is adjusting the price at which it is willing to take that type of risk. This may not be captured by loan volume nor by risk characteristics (as they are not changed). And even if the risk characteristics did change, it would take some time to show up in a bank's balance sheet. Hence, this measure of bank aggressiveness may capture changes in bank behavior more timely than balance sheet information. In addition, note that the proposed aggressiveness measure could also be related to the all-in spread, as more aggression may result in lower spreads. However, just as with loan volume, this need not be the case. This time, it need not be if other characteristics change, too. In that case the all-in spread may stay constant while other observable characteristics worsen, making the bank effectively more aggressive. Therefore, this measure of aggression may complement information obtained purely from loan volume or prices.

One potential objection against this aggressiveness approach is that it only works for large banks that are active in the syndicated loan market. Although this paper focuses on the syndicated loan market in particular, the aggressiveness measure could also be calculated for other loan categories as long as the supervisor or regulator can ensure access to timely updated information about the relevant loan category. This may widen the range of applicability substantially. However, even if it were only applicable to large banks active in the syndicated loan market the proposed measure would still be of value since these large banks are typically the ones that are systemically relevant.

To my knowledge, this is the first paper that attempts to investigate this residual of the syndicated loan spread more in detail. Esty and Megginson

(2003) and, inspired by it, De Haas and van Horen (2010) use this residual already but instead of investigating the residual itself more in detail, they only use it as a control variable and call it "loan pricing residual" and "loan residual risk", respectively. In my view, the interpretation of the residual as the loan residual risk is only valid if the markets are perfectly competitive. Once there exist some frictions like, for example, asymmetric information, the residual may not only reflect residual risk. Therefore, I prefer the interpretation of aggressiveness in a sense of willingness to make a particular loan. This willingness certainly depends on risk characteristics, too, but is not restricted to that. For instance, diversification motives and strategic changes in the lending policy may also play a role.

Another paper that investigates variations in bank loan pricing is Cerqueiro et al. (2007). It examines how banks use "discretion" in their loan rate setting process. In essence, the authors employ a heteroscedastic regression model in which the residual variance is allowed to depend on the level of the explanatory variables. The difference to my aggressiveness approach is that in Cerqueiro et al. (2007) a larger variance (the squared residual) is seen as more discretion and a small variance is interpreted as little discretion, because the loan pricing follows observable characteristics ("rules"). Hence, for the individual residual only the distance to the mean residual (which should be equal to zero) matters, as this determines the size of the variance. In my approach, not only the distance to the mean matters but also the sign of the residual. Thus, the exact location of the residual relative to the overall distribution is of interest. To illustrate the differences, consider two loans with the same residual variance. In Cerqueiro et al. (2007) these two loans exhibit the same level of discretion and are thus not distinguishable. In my approach, these two loans can be based on an identical level of bank aggressiveness if the residual is identical, or they can be based on different levels of bank aggressiveness if the absolute value of the residual is the same but not its sign. If the variance of both loans is very high, the discretion is very high but the level of aggressiveness could differ substantially. Consequently, my approach is able to examine the nature of the discretion more in detail while Cerqueiro et al. (2007) can only detect the presence of discretion.

Note, that Cerqueiro et al. (2007) also attempt to investigate the extreme residuals a bit more in detail but that they are only able to draw a few conclusions since their remaining results are too noisy. Their approach is as follows. First they create two dummies, Rip-off and Bargain, that indicate large deviations (more than one standard deviation) from the mean. Next, they estimate logit regressions of these two dummies on the same explanatory variables they have used in the discretion estimation. Their results suggest that small, opaque firms are being subsidized while firms with a bad fiscal track record face a mark-up in their loan spreads. The differences to my approach are twofold. First, by relying on the binary nature of their dependent variables, they disregard all the variation that occurs within the two categories. Instead, my approach uses all the distributional information to analyze the variations in the residual. Second, they attempt to explain the dummies with the same variables that they already used to estimate the dummies. My approach, on the other hand, introduces bank-specific variables in the second step only.

Lastly, let me relate my approach of aggressiveness in the loan pricing to a recent paper by Mason et al. (2009) that is concerned with what the authors call "business aggression". Mason et al. (2009) use high ex-post write-downs during the recent financial crisis to identify banks with "reckless" business aggression and examine whether this business aggression contributed to the recent credit crisis. Their hypothesis is that "reckless" banks make loans with fewer covenants than banks with less aggression. In addition, they assume that cov-light loans have a lower probability of default (PD) but a higher loss given default (LGD), because loans with more covenants are likely to violate one of the covenants earlier (higher PD) but in that case the repayment share is also likely to be higher (lower LGD). The authors acknowledge that in normal economic times it is difficult to distinguish the level of aggression since a certain level of losses can be the result of either high PDs combined with low LGDs or the other way around. However, during the financial crisis the covenants would no longer make a difference so that both covenant and cov-light loans failed. In this particular situation, banks with a high level of aggression and thus with a lot of cov-light loans suffered more losses, which helps the authors to identify banks with a high level of aggression. Their findings suggest that aggressive banks were not different from other banks in the period 1995 to 2001 but that they reduced covenants in the "loose" period of 2001 to 2006 substantially. There are various differences between the Mason et al. (2009) approach and mine. First, their definition of aggression focuses only on the number of covenants and no other deal characteristics. Second, their approach needs to identify losses in extreme situations ex-post in order to identify aggressive banks. My approach, on the other hand, can be applied also in normal times and does not need to wait for accounting losses to materialize. In fact, I show in the empirical section below that my measure of aggressiveness can actually be used as a leading indicator for changes in the loan book of a bank.

4.5 Data

The syndicated loan data is obtained from the Reuters LPC Dealscan database, which offers an extensive coverage of syndicated loans around the world. In particular, it contains detailed information on the contract terms, the members of the syndicate and the borrower(s). Reuters LPC collects data primarily from the attachments on SEC filings, publications from major banks, and the financial press[8]. The full Dealscan database contains 111530 observations from the year 1982 to the beginning of 2010 where data on the all-in spread, loan amount and lead arranger is available. However, since one syndicated loan can have several tranches, there are, in fact, only 72649 loan deals. 66.1% of these deals contain only one tranche, while 21.4% contain two and 12.5% contain three or more tranches.

While these tranches may differ in various characteristics, such as the loan amount, spread, and maturity (and other characteristics), I cannot treat the various tranches of one syndicated loan as independent observations. As Sufi (2007) notes, this is because the actual syndicated loan contract is drafted at the deal level so that only one contract exists, in which all lenders and covenants are listed together. Moreover, all lenders are chosen on the tranches collectively, not independently. If one treated the observations as independent, the resulting standard errors were improperly small. Following

[8] For more information on the Dealscan database see, for example, Ivashina (2009), Sufi (2007), and Carey, Post, and Sharpe (1998).

Ivashina (2009), I focus on the largest tranche of each deal.

I drop observations which are in some sense abnormal, like, for example, bilateral deals and club deals (2913)[9] and, following De Haas and van Horen (2010), loans to government entities (464). Similarly, I follow Ivashina (2009) in dropping loans to regulated (2015) and financial industries (8470), and loans, which are not completed yet (1609).

I also drop 11679 observations with multiple lead arrangers to simplify the interpretation of the aggressiveness measure. In the case of multiple lead arrangers, the obtained measure of aggressiveness represents an average of the aggressiveness of all lead arrangers. However, the exact aggressiveness of a lead arranger may differ from that average given that different lead arrangers can have different bargaining power and functions (see, for example Sufi (2007)) within the syndicate. To make sure that the measured aggressiveness is really the one desired by the lead arranger, I decided to focus on observations with only one lead arranger.

In addition, I drop observations before the year 1987 and for the year 2010 since Dealscan contains only 79 loans for the years 1982 to 1986 together and only four for 2010. Finally, I follow Sufi (2007) and drop all deals where none of the top 100 lead arrangers is involved (5213) to make the collection of lead arranger specific data manageable. The final sample therefore contains 40203 observations over the years 1987 to 2009.

Table 2 presents summary statistics for the variables used in the estimation of the lead arrangers' aggressiveness. The dependent variable is the all-in spread drawn and it has a mean of 207 basis points and a median of 200 basis points. Among the independent variables the natural logarithm of sales has a mean of 21.24 and a median of 19.49, which translates into $1,680 million and $291 million, respectively. Sales are not reported in roughly one third of the cases so that I also include a dummy if the sales are not reported. Borrowers have a ticker symbol in 40 percent of the cases, a rating in 23 percent of the cases but a commercial paper rating in only 6 percent of the cases. Furthermore, roughly 28 percent of the borrowers obtained a syndicated loan in the previous three years and on average the borrowers had 1.4

[9] De Haas and van Horen (2010) note that club deals are special as they lack the typical two tier structure.

syndicated loans before. The largest tranche of the deal (which I consider in this paper) is secured in 38 percent of the cases, has financial covenants in 29 percent and performance pricing in 22 percent of the cases, and is a term loan in 32 percent of the cases. The mean log of the tranche amount is 19 with a median of 18.13, which translates into $179 million and $75 million, respectively. The average number of facilities of the whole deal is 1.48 with a median of one.

Among the chosen maturities the category two to five years is the preferred choice in 53 percent of the cases, followed by the omitted category (less than two years and no revolver or a revolver with more than one and less than two years) with 23 percent, maturities longer than five years with 17 percent, and revolvers with less than one year maturity in seven percent of the cases. Within the category loan purpose, general corporate purposes are stated most often (49 percent), followed by the omitted category (17 percent), debt repayment (16 percent), acquisitions (13 percent), and backup lines (4 percent). The information on the lead ranking is left out as it is naturally skewed to the left since the number one lead arranger, by definition, has the most deals arranged. Finally, the lead reputation, defined as the market share (based on the total amount arranged) of the previous year has a mean of 7 percent and a median of three percent.

4.6 Results

4.6.1 Estimating Aggressiveness

To estimate banks' aggressiveness in the syndicated loan market, I estimate equation (4.1) and take the residuals as the banks' aggressiveness. The results of the regression are shown in Table 3. Note that I added two dummies, one for cases in which the sales were not reported and one for cases, in which information whether a loan is secured or unsecured was not available. In general, most of the coefficients are significant with the expected signs. Higher sales and a ticker symbol reduce the spread of a syndicated loan as they represent lower information asymmetries. A rating worse than BBB tends to increase the spread while the opposite is true for ratings better than BBB. Similarly, not having a rating increases the spread but having a commercial paper rating reduces it. While a previous interaction between lead arranger and borrower slightly reduces the spread, the sign for borrower reputation is contrary to the expectation. Instead of reducing the spread it tends to slightly increase the spread. A potential explanation for this might be correlation with, for example, *Previous Relationship.* In roughly 80% of the deals the borrower had at most two previous loans and if those occurred in the last three years, this might also be captured by the *Previous Relationship* dummy. The signs of the remaining variables are in accordance with the theoretical expectations from Table 1. A secured loan tends to have higher spreads than an unsecured loan and performance pricing, a larger amount, a longer maturity, and a better lead reputation tend to decrease the spread. Term loans and loans with more facilities, on the other hand, are associated with higher spreads. Only financial covenants tend to have no influence on the spread and short maturities seem to be no different than maturities between one and two years. All in all, the coefficients and their signs seem reasonable so that I can now turn to the actual aggressiveness measure.

4.6.2 Does Aggressiveness differ among Banks?

To answer the question whether aggressiveness differs among banks, several dimensions are investigated. As a start, I calculate the average aggressiveness per bank across all years of existence by weighting each observation by its tranche amount. Figure 1 shows the averages for the top 100 lead arrangers. The number one in the ranking is defined as the lead arranger that has arranged the largest number of deals during the entire sample period. One can see in Figure 1 that the average aggressiveness varies considerably among the banks without having too many outliers. Keeping in mind that negative values imply more aggressiveness (lower spreads), the figure seems to suggest a slightly downward sloping trend. This suggests that the largest lead arrangers can afford to be less aggressive. In unreported results, I test this more formally by regressing the average aggressiveness of each lead arranger upon its rank. The coefficient of the rank is negative but insignificant so that I cannot conclude that better ranked lead arrangers are on average less aggressive than lower ranked competitors.

Next, the individual bank aggressiveness is investigated over time. Since plotting the yearly aggressiveness of all 100 lead arrangers over time in one graph is not very instructive, I focus here on the top 10 lead arrangers. Again, the top 10 lead arrangers are defined as those 10 banks that arranged the largest number of deals across the entire sample period. One can see in Figure 2 that there are persistent differences in aggressiveness over time even among the top 10. For example, number three and ten among the top 10 lead arrangers differ in their aggressiveness by more than 50 basis points for most years of the sample. This suggests that the findings in Figure 1 are not due to one or two outlier years but rather the result of bank-specific differences that are quite persistent over time. Moreover, it can be seen that the aggressiveness differences are larger in the first part of the sample, then they tend to converge a bit around the year 1999 before they widen slightly in the following years and increase substantially in the last years of the sample. The first part could be explained by a lower number of observations. However, since the number of observations is lower in the first years for all top 10 lead arrangers and there does not seem to be a systematic difference between banks with large swings and banks with small swings a lower number of observations alone cannot explain the larger swings in the beginning.

Another potential explanation is idiosyncratic pricing. It is possible that banks needed some time to fine-tune their pricing. However, in this case we should observe a steady decline in the swings and in the standard deviation of the yearly aggressiveness measure. As one can see in Figure 3, this is not fully true. In the late 1980's and early 1990's the standard deviations of the top 10 lead arrangers do converge among each other but decline only somewhat in absolute value. In addition, after 1999 their dispersion and levels seem to increase again, especially after 2007. The latter observation hints to another candidate, namely business cycle movements. In both figures, there is a substantial increase in the years 2008 and 2009, implying that lead arrangers became less aggressive on average but also that their pricing became more dispersed within a bank. However, when the time series behavior of Figures

2 and 3 is compared with the GDP growth in Figure 4 one has to conclude that for most years of the sample the U.S. GDP growth is not related to the levels and dispersion of the lead arranger aggressiveness measure. Only in the last two years, where the U.S. experienced a severe recession, the U.S. GDP growth is negatively correlated with the levels and standard deviations of the top 10 lead arranger aggressiveness. This implies that during the recession the banks become substantially less aggressive and more discriminative in their pricing but this holds only for the most severe recession since the great depression. Overall, one has to conclude that there may be several factors that explain the variation of the top 10 lead arranger aggressiveness over time.

In order to rule out that the findings only hold for the top 10 lead arrangers, I repeat the analysis for the whole sample. In this case, however, I cannot look at individual lead arrangers anymore but have to look at the average aggressiveness of all banks over time. Since the aggressiveness measure averaged over the whole sample should be zero by construction, the average across all banks per year will be closer to zero already. Nevertheless it may be possible to detect some trends over time. Figure 4 plots the average yearly aggressiveness of all banks and the U.S. GDP growth rate over time while Figure 5 repeats the exercise for the standard deviation of the yearly aggressiveness of all banks. In general, the results from the top 10 lead arrangers are confirmed for the whole sample. Across the largest part of the sample the average yearly aggressiveness of all banks does not seem to be related to the U.S. business cycle. Only in the last two years a strong negative relationship is visible. The same holds true for the standard deviation of the yearly aggressiveness of all banks. In the early years the standard deviation declines irrespective of the business cycle up until the year 2000. Afterwards, the standard deviation seems to be more related to the U.S. GDP growth since a decline in economic activity is associated with a rise in the standard deviation. Hence, also for the whole sample, it seems that banks become substantially less aggressive and more discriminative in their pricing during the recent recession.

Another important dimension is the time series behavior of the most and least aggressive lead arrangers. Figure 6 depicts the average yearly aggressiveness of the three most and three least aggressive lead arrangers over time. For that, each year the three most and least aggressive leads are determined. This method is preferred to one where the three most and least aggressive leads are determined at the beginning and then followed over time as they might have changed their business behavior, merged or simply ceased to exist. Instead, this method follows the industry's most extreme actors over time. One can see in Figure 6 that there is a clear difference between the three most and three least aggressive banks at any point in time. In addition, this difference seems to vary over time in a similar fashion as the behavior of the top 10 lead arrangers over time. During the first half of the sample it tends to shrink until the year 1999 while afterwards it widens somewhat. Particularly the last two years are distinctive again, as the difference between the most and least aggressive actors widens substantially. Moreover, one can observe that the dispersion within the least aggressive lead arrangers is larger than among the most aggressive lead arrangers. This seems to be plausible as the most aggressive banks operate at the frontier of what is possible, which implies that competition forces the lead arrangers to be close to each other. For the least aggressive banks on the other side there is no clear frontier so that the dispersion may be larger.

In order to make sure that these observations do not hold only for the three most extreme lead arrangers on each side, I repeat this exercise for the five and ten most and least aggressive lead arrangers. To maintain the clarity of the figure, I take the average yearly aggressiveness of the five and ten most and least aggressive lead arrangers, respectively. The results are shown in Figure 7. The difference between the ten most and ten least aggressive lead arrangers is, as expected, even larger than among selected members of the top 10 lead arrangers. However, it is somewhat smaller than the difference between the three (and five) most and least aggressive lead banks. Across most years of the sample, it varies about 150 basis points or more. In addition, the previously described trends are clearly visible, too. In the first half the difference between the most and least aggressive banks shrinks until the year 1999, afterwards it tends to increase a bit again, and the impact of the recession in the last years is again very visible.

The analysis of the top 10 lead arrangers, all lead arrangers, and the most and least aggressive lead arrangers presents one consistent picture. Throughout the sample there is considerable variation of aggressiveness over time and among banks. Especially the variation among banks suggest that seemly identical borrowers can face different loan spreads depending on the aggressiveness of the bank. This implies a certain degree of allocative inefficiency given that the differences can be as large as 50 basis points even among the top 10 lead arrangers. In addition to the variation among banks, there exists also considerable variation over time, which cannot be attributed to a single factor. While idiosyncratic pricing may explain the early years of the sample, other factors, like for example, the business cycle play a role in the later years and especially in the big recession at the end of the sample. However, there may also be bank-specific factors at play, which is why in the next section, I analyze bank-specific determinants more in detail.

4.6.3 Determinants of Aggressiveness

The question whether there exists a link between a lead arranger's aggressiveness and its bank-specific characteristics is of interest for several reasons. First, it is in general important to understand pricing factors of loans, especially for policy makers and supervisors, since a proper understanding of, for instance, changes in loan spreads helps to determine the correct policy reaction. It also facilitates the monitoring of the financial system and helps to react in a timely fashion. Second, knowledge about such a link may be important for regulation in particular. If, for example, a bank's aggressiveness is related to other risk taking channels like, for instance, leverage, then regulating leverage alone might not have the desired effect. In addition, it may be possible that banks with access to, for instance, securitization or derivatives markets may act more aggressive in the syndicated loan market. In that case, tightening the regulating of the securitization or derivatives markets may have an economic impact on the syndicated loan market, which in turn may make loans more expensive and hence have an effect on economic activity.

In this section I analyze potential determinants of aggressiveness, that is, bank-specific characteristics that influence a lead arranger's aggressiveness.

The analysis is done by using a fixed effects panel data approach with standard errors clustered at the bank level. In particular, I regress the average yearly aggressiveness per bank $\varepsilon_{i,t}$ upon lagged yearly bank characteristics $W_{i,t-1}$:

$$\varepsilon_{i,t} = \delta + \eta W_{i,t-1} + \theta_i + \mu_{i,t}, \tag{4.2}$$

while including bank fixed effects. For the former variable I take the estimates obtained in section (4.6.1). The bank-specific characteristics, however, are not reported in the Dealscan database so that I first need to match the top 100 lead arrangers from Dealscan with the Bankscope database. The latter offers a broad coverage of harmonized financial data for financial institutions around the world. Although not always as detailed as the information from a national supervisor, Bankscope represents a good mix between detailed information and global coverage. Based on the Bankscope database, I was able to identify in total 85 entities, among which also a few newly founded ones as a result of a merger. I treat two merged firms as a new entity because it cannot be guaranteed that the past business style, and hence the past aggressiveness, will be continued after the merger. Moreover, I drop banks with less than four years of data. In addition, some banks which ceased to exist in the early period of my sample can still be found in Bankscope but have no longer detailed balance sheet information available. Because of these two facts, I end up with 69 lead arrangers for which I have at least four years of data. Note, however, that in some cases the number of lead arrangers falls even further since some balance sheet variables are not reported for all lead arrangers.

Table 4 presents summary statistics for the selected balance sheet variables. The mean of total assets is roughly \$161 billion with a median of \$190 billion, which translates into 11.99 and 12.16 when taking logs of total assets. The fact that the median is actually higher suggests that there are a few small banks in the sample. However, in unreported results, I exclude the small banks such that the mean and the median are roughly equal and find that this does not influence the results shown below. The ratios debt to total assets and loans to total assets have a mean of 0.94 and 0.53, respectively, and very similar medians. Off-balance sheet items as a share of total assets have a mean of 0.14, which seems to be driven by a few banks with larger shares since the median is only 0.09. A similar observation can be made when looking at the ratio liquid assets to total assets, whose mean is 0.12 but whose median is only 0.09. The return on assets have a mean and median that are close to each other with 0.89 and 0.91 percent, respectively. Among the loan quality proxies, the loan loss provisions are on average 0.65 percent of total loans and the loan loss reserves are 2 percent of total loans. The share of nonperforming loans to total loans is on average 1.8 percent, which seems to be driven by a few observations with larger shares as the median is only 1.1 percent. On the liabilities' side, banks finance themselves mostly with short term funding, which makes up on average 78.6 percent of total debt. Among the short term funding, nondeposits make up only 14 percent on average. Lastly, the banks in the sample have a mean tier 1 capital ratio of 8.4 percent with a median of 8.2 percent.

The results from the regression in equation (4.2) are shown in Table 5. In the first column the average yearly aggressiveness is regressed upon three explanatory variables, namely size, leverage and the loan-to-asset ratio. In the following columns, various other characteristics are added and in the last columns all variables are included with the exception of the ratio nonperforming loans to loans since it is highly correlated with the ratio loan loss reserves to loans.

Across all columns one can observe that size is positively related to the aggressiveness measure $\varepsilon_{i,t}$. Remembering that a more positive value of $\varepsilon_{i,t}$ implies less aggressiveness, this suggests that larger banks tend to be less aggressive. The debt to asset ratio, on the other hand, is in most cases negatively related to the aggressiveness measure. This, however, is most likely not a causal relationship but instead both variables seem to be driven by a third factor, namely the overall risk appetite. In that case, a bank with a high overall risk appetite chooses a high leverage ratio and an aggressive pricing approach. The third permanent explanatory variable, the loan-to-asset ratio, is not related to aggressiveness. In unreported results,I also test the lagged loan growth instead of the lagged loan levels but they, too, are insignificant.

Columns two and three reveal that off-balance sheet items as a ratio of total assets, the return on average assets, and liquid asset to total assets are not related to aggressiveness. Columns four to eight investigate loan quality proxies a bit more in detail. They show that especially loan loss provisions as a share of total loans are significantly related to aggressiveness, both alone and in combination with loan loss reserves or nonperforming loans. Higher provisions the year before suggest a less aggressive behavior in the current year. This is one of the central results of the paper as it shows that when problems in the loan book arise, banks do not just reduce quantity but also adjust the pricing. The latter may occur when the bank is committed to providing a certain amount of capital but both may actually also go hand in hand. In terms of economic significance, a coefficient of 1200 implies an increase in the spreads (lower aggressiveness) of roughly 7 basis points when the ratio loan loss provisions to total loans increases by one standard deviation and all other variables are kept constant. Given that these 7 basis points are the result of only one factor, namely the loan loss provisions, this increase seems to be meaningful.

The next loan quality proxy, the loan loss reserves as a share of total loans, is insignificant. This is not unreasonable since the provisions are a flow variable and the reserves a stock variable. The flow variable therefore represents the recent changes during the last year while the stock variable is a summary of all past events, among which some may cancel each other out. In addition, the stock variable is influenced by new inflows (through provisions) but also through outflows (through charge-offs). A zero change in the reserves can hence be the result of no provisions and no charge-offs or large provisions and charge-offs of equal size.

For these reasons, I also test an alternative to the loan loss reserves, namely the share of nonperforming loans to total loans. Columns six and eight reveal that they are insignificant alone and in combination with the loan loss provisions. The fact that only the loan loss provisions are significant makes intuitively sense because they are the first indicator showing that something is wrong while others (loan loss reserves and nonperforming loans) take more time to react. Hence, when provisions increase a bank may react by being less aggressive. This may take less time than the time it takes for nonperforming loans to change, for example. Theoretically higher lags in variables like, for instance, loan loss reserves or nonperforming loans may reveal a significant relationship but in this case there may be more confounding effects in the meantime. In addition, the aggressiveness measure should react relatively quickly to changes in a bank policy, so that lag of one year may not be long enough while a lag of two years may already be too long. Therefore, I do not investigate higher lags further. Instead, I turn to potential determinants on the liabilities' side. Columns nine and ten show that neither the share of short term funding to total debt nor the share of nondeposit funding to short term funding is significant at conventional levels. It implies that the liabilities structure does not seem to influence a bank's aggressiveness.

The last column includes all tested variables at once, except for the ratio nonperforming loans to loans since it is highly correlated with the ratio loan loss reserves to loans. The results do not change much. Larger banks still seem to be less aggressive although the significance of size declines somewhat. Higher leverage and more aggressiveness continue to be significantly related, too. The loan loss provisions as a share of total loans continue to be significant at the 5% level and with a similar coefficient. All other explanatory variables remain insignificant. Lastly, note that the number of banks varies a bit as not all balance sheet variables are reported all the time. Additional tests (not shown here), however, show that this does not influence the results.

The combined results suggest that bank specific factors form a large part of the pricing residual so that one can speak of a bank's aggressiveness in a narrower sense. Unobserved borrower characteristics might only have an influence on the residual if they were systematic across a bank's loan portfolio and not just idiosyncratic to the specific loan. In that case, however, they should be at least partially captured by the industry and country dummies in the pricing regression. Moreover, in the second step, they should be capture by the bank fixed effects, so that overall, their influence should be small. The fact, that bank specific factors play a significant role in explaining aggressiveness while the general business cycle does not, supports the interpretation of aggressiveness in a narrower, bank-specific sense.

4.6.4 Aggressiveness as a Leading Indicator

This section addresses the question whether a bank's aggressiveness can be used as a leading indicator. More precisely, I analyze if lags of the aggressiveness measure are related to recent changes in certain balance sheet items. Let me stress very clearly here, that I am not interpreting the results in a causal way. In order to use the aggressiveness as a leading indicator it is sufficient that its lags are related to recent changes in the balance sheet variables even if both are driven by a third factor. Even in this case, using the aggressiveness measure as a leading indicator is interesting for supervisory and regulatory purposes. This is because the balance sheet information that supervisors and regulators often rely on are reported with a delay as they are reported only every 3 months. In addition, there is widespread evidence that banks strategically manage the reporting of their loan loss data (Wall and Koch (2000), and Hasan and Wall (2004)), delay the provisioning for loans until cyclical downturns have already set in (Laeven and Majnoni (2003)), and overstate the value of distressed assets (Huizinga and Laeven (2009)). For these reasons it may be useful to have a leading indicator at hand that informs the regulator or supervisor about potential changes in the balance sheet of a bank in a more timely fashion.

The proposed aggressiveness measure should be a more timely indicator since information about syndicated loans is published immediately after the deal is closed through the league tables. As Ivashina (2009) notes, lead arrangers have a strong incentive to publish this information as it serves as a marketing tool. Therefore, it should be relatively quick and easy to collect and update this information in an database and, in fact, this is exactly what the Dealscan database does. In addition to having access to this database, the aggressiveness measure itself should also be a timely indicator. Given that changes in the aggressiveness measure represent changes in the pricing behavior, this requirement should be satisfied, because the pricing of a loan changes as quick as or even quicker than the loan volume. The latter situation may occur if the bank has already informally committed itself to a certain loan volume. However, even if the loan volume and the pricing changed with the same pace, this information should still be more timely than the balance sheet information that is published every 3 months.

Table 6 reports the results for the regressions in which the one-year change in the balance sheet variable is regressed upon three lags of the aggressiveness measure. In addition, the level of the last year balance sheet variables is included to control for mean reversion. It turns out that neither of the three lags is significantly related to changes in bank size, the debt-to-asset ratio, the loan-to-asset ratio, as well as the ratio short term funding to total debt. Since the three lags may be correlated to each other, I also check (in unreported results) each lag individually but the results remain unchanged. The return on assets, however, seem to be significantly related with the one year lag of aggressiveness. In a causal interpretation one could say that a bank that has been less aggressive the year before experiences higher return on assets now. Most likely, however, there is general effort to improve profitability which expresses itself first in, among others, less aggressive pricing. After a while the benefits can be seen in improved return on assets. Liquid assets as a share of total assets, on the other hand, are significantly related to the third lag of aggressiveness, suggesting that a bank that has been less aggressive three years ago experienced a growing share of liquid assets in the last year. A potential explanation for this may be a general switch in the bank's aggressiveness which leads first to less aggressive pricing and later on to more liquid assets. A potential reason why the liquid assets may react with a delay is that the bank may be committed to a certain loan volume already and that it may take time for these commitments to fade out.

The next group of variables deals with the loan quality of a bank. The loan loss provisions as a share of total loans are not significantly related with either of the three lags. Again, in unreported results I tested each lag individually but the results remain unchanged. The ratio of loan loss reserves to total loans, however, is significantly related to the first and third lag of aggressiveness. The reason why the second lag is not statistically significant may lie in some small collinearity issues among the lags because when testing each lag alone (not reported here), the second lag turns significant at the 5% level while the first lag is significant only at the 10% level. Thus, it seems that banks that have been less aggressive over the last three years can also afford to have declining loan loss reserves, which may be due to a general trend towards a more conservative banking approach. The ratio of nonperforming loans to total loans is significantly related to the third lag of aggressiveness at the 10% level. However, this result vanishes once each lag is investigated individually so that I do not want to interpret this finding any further.

The last variable to consider is the Tier one capital ratio. The results suggest that a bank that has been less aggressive over the last three years also experiences an improving Tier one capital ratio, as the first and third lag of aggressiveness is significant at the 5% level. Tested individually, the second lag also turns significant but only at the 10% level. These findings could be the result of a general move towards more conservatism under which the syndicated loan pricing becomes less aggressive and the capital buffer is improved. Finally, let me note that the level of the last year balance sheet variable is always negative and significant, which confirms the expectation of trends towards mean reversion.

Overall, the results suggest that the lagged aggressiveness of a bank is related to changes in some key balance sheet items, including a meaningful economic significance. As an example, take a decrease in aggressiveness of one standard deviation (roughly 59 basis points) and multiply it with the sum of the coefficients of the three lags of aggressiveness. When considering the loan loss reserves as a share of total loans, this translates into a decrease of this ratio of roughly 8.1%[10]. Similarly, for the Tier one capital ratio, this translates into an improvement of the ratio of 4.7 %[11]. Given that these changes stem only from the syndicated loan part of the loan portfolio, these changes are economically meaningful. This is also of interest for a supervisor or regulator as it suggests that the aggressiveness of bank can be used as an leading indicator for coming changes in a bank's balance sheet items like, for instance, the share of loan loss reserves or the Tier one capital ratio. Particularly in cases, where the supervisor requires a bank to improve its capital position or to improve the quality of the loan book, the aggressiveness measure might be helpful early information whether the bank follows suit well before the taken measures materialize in the respective balance sheet

[10] The sum of all three coefficients is -0.00002951, which multiplied by 59 is roughly equal to -0.00174. Evaluated at the mean loan loss reserves ratio (0.0215), this yields -0.081.

[11] The sum of all three coefficients is 0.00673, which multiplied by 59 is roughly equal to 0.39707. Evaluated at the mean Tier one capital ratio (8.5), this yields 0.0467.

items. To further improve the informational value of the leading indicator a supervisor or regulator could require banks to submit detailed data on all loan categories. In addition, examining aggressiveness more in detail in future research could also help to understand the interplay between risk appetite and aggressiveness, and the interplay between quantity adjustments and pricing aggressiveness in the loan market.

4.7 Conclusion

This paper investigates the pricing behavior of large, international lead arrangers in the syndicated loan market. In particular, it proposes to use the residual of a pricing regression as a measure of a lead arranger's aggressiveness. After regressing the all-in spread of a syndicated loan on borrower characteristics, loan characteristics, and lead arranger characteristics, the obtained residual is investigated across several dimensions.

Based on detailed information from the Reuters LPC Dealscan database on 40203 syndicated loans for the years 1987 to 2009 I find that there is considerable variation of aggressiveness over time and among banks. Especially the variation among banks suggest that seemly identical borrowers can face different loan spreads depending on the aggressiveness of the bank. This implies a certain degree of allocative inefficiency given that the differences can be as large as 50 basis points even among the top 10 lead arrangers while in an efficient outcome the difference should be zero. The time series variation seems to be explained best by idiosyncratic pricing in the first half of the sample. In the latter half, other factors seem to be more important. Business cycle movements, however, do not seem to be related to the time series variation as they only seem to influence it in the last years of the sample when the recent economic recession hit the world economy.

Therefore, the paper examines bank-specific factors more in detail. For this, I obtain bank-specific balance sheet information from the Bankscope database and regress the average yearly aggressiveness per bank upon lagged yearly bank characteristics. I find that especially loan loss provisions as a share of total loans are significantly related to aggressiveness. Higher provisions the year before suggest a less aggressive behavior in the current year.

This result suggests that when problems in the loan book arise, banks do not just reduce quantity but also adjust the pricing.

My findings also suggest that the aggressiveness measure can indicate future changes in a bank's condition, which makes it interesting for supervisory and regulatory processes. Supervisors and regulators often have to rely on bank-specific balance sheet information to inform themselves about the condition of a bank. This balance sheet information, however, is typically reported with a lag so that there may be informational value in having a more timely update about the condition of a bank. A bank's aggressiveness seems to be one such more timely indicator because I find that less pricing aggressiveness is related to increasing return on assets in the short run (one year) and a lower share of loan loss reserves to total loans and a higher Tier one capital ratio over the short and medium term (one to three years).

4.8 Tables

Table 1: Definition and Expected Sign of Explanatory Variables

Variable Name	Description	Exp. Sign
Borrower Characteristics W		
Sales	ln(sales) of borrower	–
Ticker	dummy=1 if borrower has a ticker symbol	–
Credit Ratings	set of dummies: one for each Standard & Poor's senior debt rating, BBB is the omitted category	lower spreads for better ratings
Not Rated	dummy=1 if borrower is not rated	+
CP Rating	dummy=1 if borrower has a CP rating	–
Previous Relationship	dummy=1 if over the last 3 years the same lead arranged a loan for the same borrower	–
Borrower Reputation	number of loans borrower obtained before	–
Industry	dummies at two-digit SIC level; N/A is the omitted category	varies
Country	country dummies for the country of the borrower; USA is the omitted category	different
Loan Characteristics X		
Secured	dummy=1 if loan is secured	+
Financial Covenants	dummy=1 if financial covenants exist	ambiguous
Performance Pricing	dummy=1 if performance pricing exists	ambiguous
Amount	ln(amount) of the tranche	ambiguous
Number of Facilities	number of facilities that a deal has	ambiguous
Short Maturity	dummy=1 if loan is a revolver and has a maturity of less than 365 days	–
Intermed Maturity	dummy=1 if maturity ranges from 2 - 5 years	ambiguous
Long Maturity	dummy=1 if maturity exceeds 5 years	ambiguous
Term	dummy=1 if loan is a term loan	+
Loan Purpose	4 dummies for general corporate purposes, debt repayment, acquisition, and backup lines; all other purposes form the omitted category	different
Lead Characteristics Z		
Lead Ranking	lead's ranking based on market share using the number of deals (in previous year)	+
Lead Reputation	market share (% of amounts) in previous year	–

Table 2: Summary Statistics for Variables used in Aggressiveness Estimation

Variable	Mean	Std. Dev.	10^{th} Perc.	50^{th} Perc.	90^{th} Perc.
Dependent Variable					
All-in spread drawn	206.57	127.91	50.00	200.00	355.00
Independent Variables from Table 1					
Sales	21.24	22.90	17.33	19.49	21.84
Ticker	0.40	0.49	0	0	1.00
Not Rated	0.77	0.42	0	1.00	1.00
CP Rating	0.06	0.24	0	0	0
Previous Relationship	0.28	0.45	0	0	1.00
Borrower Reputation	1.40	2.12	0	1.00	4.00
Secured	0.38	0.49	0	0	1.00
Financial Covenants	0.29	0.45	0	0	1.00
Performance Pricing	0.22	0.41	0	0	1.00
Amount	19.00	19.85	16.30	18.13	19.81
Number of Facilities	1.48	0.86	1.00	1.00	3.00
Short Maturity	0.07	0.26	0	0	0
Intermed Maturity	0.53	0.50	0	1.00	1.00
Long Maturity	0.17	0.37	0	0	1.00
Term	0.32	0.47	0	0	1.00
General Corporate Purpose	0.49	0.50	0	0	1.00
Debt Repayment	0.16	.037	0	0	1.00
Acquisitions	0.13	0.33	0	0	1.00
Backup Lines	0.04	0.19	0	0	0
Lead Reputation	0.07	0.08	0.001	0.03	0.19
Additional Information					
Sales in $ mil.	1,680.00	8,860.00	33.70	291.00	3,040.00
Dummy No Sales Reported	0.35	0.48	0	0	1.00
Trancheamount in $ mil.	179.00	416.00	12.00	75.00	400.00

Table 3: Regression to estimate Aggressiveness

Variables	Coefficient
Sales	-8.083*** (0.510)
Dummy Sales not available	-146.9*** (9.784)
Ticker	-12.00*** (1.246)
Dummy S&P Rating = D	137.1*** (9.745)
Dummy S&P Rating = C	112.1** (46.53)
Dummy S&P Rating = CC	158.4*** (27.98)
Dummy S&P Rating = CCC-	137.0*** (19.68)
Dummy S&P Rating = CCC	164.3*** (17.02)
Dummy S&P Rating = CCC+	128.8*** (10.28)
Dummy S&P Rating = B-	95.08*** (6.617)
Dummy S&P Rating = B	72.92*** (4.946)
Dummy S&P Rating = B+	64.23*** (3.901)
Dummy S&P Rating = BB-	43.26*** (3.762)
Dummy S&P Rating = BB	33.79*** (4.446)
Dummy S&P Rating = BB+	28.79*** (4.165)
Dummy S&P Rating = BBB-	11.18*** (3.550)
Dummy S&P Rating = BBB+	-6.533* (3.372)
Dummy S&P Rating = A-	-16.04*** (3.413)
Dummy S&P Rating = A	-25.02*** (3.401)
Dummy S&P Rating = A+	-29.44*** (4.309)
Dummy S&P Rating = AA-	-22.25*** (5.002)
Dummy S&P Rating = AA	-24.04*** (5.636)
Dummy S&P Rating = AA+	-42.85*** (9.860)
Dummy S&P Rating = AAA	-28.07*** (7.645)

to be continued on next page

Variables (cont.)	Coefficient (cont.)
Not Rated	27.89***
	(2.688)
CP Rating	-12.79***
	(2.505)
Previous Relationship	-3.795***
	(1.257)
Borrower Reputation	2.684***
	(0.298)
Secured	46.08***
	(1.507)
Unsecured	-19.18***
	(1.807)
Financial Covenants	1.768
	(1.743)
Performance Pricing	-32.07***
	(1.614)
Amount	-19.24***
	(0.554)
Number of Facilities	19.56***
	(0.747)
Short Maturity	-3.018
	(2.359)
Intermed Maturity	-15.48***
	(1.457)
Long Maturity	-30.09***
	(2.160)
Term	36.50***
	(1.560)
Dummy Corporate Purposes	-25.42***
	(1.760)
Dummy Debt Repayment	-28.90***
	(2.015)
Dummy Acquisitions	-12.47***
	(2.059)
Dummy Backup Line	-56.95***
	(2.831)
Lead Reputation	-52.93***
	(6.829)
Constant	677.3***
	(11.22)
Observations	40203
R-squared	0.385

The dependent variable is the all-in spread. Robust standard errors are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 4: Summary Statistics for Balance Sheet Variables

Variable	Mean	Std. Dev.	10^{th} Perc.	50^{th} Perc.	90^{th} Perc.
Total Assets in $ mil.	161,135.35	3.8954	32,299.27	190,593.85	840,035.98
Log(Total Assets)	11.9900	1.3598	10.3828	12.1579	13.6412
Debt/Total Assets	0.9359	0.0273	0.8999	0.9362	0.9684
Total Loans/Total Assets	0.5327	0.1549	0.2969	0.5487	0.7202
Off-Balance Sheet Items/Total Assets	0.1368	0.1312	0.0000	0.0893	0.3428
Return on Assets in %	0.8889	0.6583	0.2400	0.9100	1.6300
Liquid Assets/Total Assets	0.1167	0.1238	0.0014	0.0862	0.2761
Loan Loss Provisions/Total Loans	0.0065	0.0057	0.0015	0.0051	0.0130
Loan Loss Reserves/Total Loans	0.0208	0.0146	0.0091	0.0172	0.0361
Nonperforming Loans/Total Loans	0.0179	0.0181	0.0039	0.0108	0.0429
Short Term Funding/Debt	0.7860	0.1326	0.5894	0.8139	0.9301
Nondeposits/Short Term Funding	0.1441	0.1150	0.0027	0.1326	0.2649
Tier 1 Ratio in %	8.4101	1.7049	6.5650	8.2200	10.6000

Table 5: Determinants of Aggressiveness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Size	18.63***	17.97***	18.22***	18.96***	17.37***	21.19***	16.73***	19.96***	15.52**	15.45**	12.60*
	(5.658)	(5.539)	(6.279)	(5.716)	(5.711)	(4.331)	(5.886)	(4.497)	(6.216)	(6.552)	(6.756)
Debt/TA	-513.1**	-573.2**	-567.1**	-499.6**	-607.8**	-566.7**	-599.7**	-578.0**	-520.4**	-524.1**	-685.5***
	(244.1)	(256.1)	(267.9)	(234.4)	(242.8)	(225.5)	(226.3)	(220.8)	(243.4)	(250.5)	(252.8)
Loans/TA	-6.077	-9.670	-22.52	-1.881	-1.452	22.86	1.872	27.23	1.130	1.732	5.019
	(37.95)	(37.85)	(37.54)	(39.25)	(38.98)	(34.45)	(39.70)	(35.89)	(38.19)	(37.92)	(39.92)
OBS/TA		11.76	12.98								9.222
		(34.15)	(35.23)								(35.23)
ROAA		-8.133	-7.706								-5.109
		(5.677)	(6.052)								(5.929)
Liquid Assets/TA			-21.80								5.566
			(76.03)								(81.02)
Loan Loss Prov./Loans				1184**			1234**	936.4**			1152**
				(534.5)			(530.7)	(444.4)			(543.0)
Loan Loss Res./Loans					200.5		76.78				86.90
					(321.3)		(326.3)				(313.6)
Non-perf. Loans/Loans						307.8		122.7			
						(216.5)		(246.5)			
ST Funding/Debt									-62.17	-63.29	-66.01
									(68.75)	(71.42)	(74.68)
Nondeposits/ST Funding										4.420	27.92
										(53.87)	(55.40)
Constant	254.9	326.9	327.3	228.8	352.7	255.2	346.1	275.9	344.2	348.5	525.9*
	(263.4)	(282.8)	(303.6)	(256.0)	(270.7)	(235.4)	(255.5)	(233.4)	(278.0)	(291.1)	(300.7)
Observations	613	613	593	613	596	564	596	564	613	613	577
Number of Banks	69	69	67	69	68	67	68	67	69	69	67
R-squared	0.062	0.065	0.067	0.073	0.061	0.082	0.072	0.087	0.065	0.065	0.077

The dependent variable is the bank specific average yearly measure of aggressiveness and the independent variables are the yearly bank-specific balance sheet characteristics lagged by one year. Clustered standard errors (at the bank level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 6: Aggressiveness as Predictor of Changes in Balance Sheet

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ΔSize	ΔDebt/TA	ΔTL/TA	ΔROAA	ΔLA/TA	ΔLLP/TL	ΔLLR/TL	ΔNPL/TL	ΔSTF/Debt	Δ T1 Ratio
Lag Aggress.	-0.000255	-1.66e-05	-4.22e-05	0.000975**	1.45e-05	-5.81e-06	-8.47e-06**	2.95e-06	-4.46e-05	0.00372***
	(0.000243)	(1.21e-05)	(4.96e-05)	(0.000421)	(3.86e-05)	(4.12e-06)	(3.97e-06)	(5.76e-06)	(3.75e-05)	(0.00102)
Lag 2 Aggress.	0.000275	-4.21e-06	-1.86e-05	5.44e-05	4.04e-05	-7.58e-06	-7.34e-06	-4.34e-06	1.35e-05	0.00123
	(0.000183)	(8.81e-06)	(3.34e-05)	(0.000349)	(3.25e-05)	(5.36e-06)	(5.21e-06)	(8.36e-06)	(3.89e-05)	(0.00104)
Lag 3 Aggress.	-4.70e-05	3.11e-07	3.94e-05	4.35e-05	9.25e-05**	-1.53e-06	-1.37e-05**	-1.12e-05*	7.18e-06	0.00178**
	(0.000157)	(9.05e-06)	(3.02e-05)	(0.000361)	(4.38e-05)	(3.76e-06)	(6.16e-06)	(6.24e-06)	(3.05e-05)	(0.000829)
Constant	1.625***	0.355***	0.124***	0.630***	0.0600***	0.00373***	0.00750***	0.00532***	0.227***	4.464***
	(0.363)	(0.0656)	(0.0197)	(0.0886)	(0.0147)	(0.000431)	(0.00114)	(0.000576)	(0.0415)	(0.571)
Lag Level of BS Variable	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	460	460	460	460	444	460	449	430	460	461
No. of Banks	67	67	67	67	65	67	67	65	67	67
R-squared	0.106	0.172	0.124	0.255	0.283	0.202	0.267	0.202	0.125	0.238

The dependent variable is mentioned beneath each column number. TL=Total Loans; TA=Total Assets; LA=Liquid Assets; LLP=Loan Loss Provisions; LLR=Loan Loss Reserves; NPL=Nonperforming Loans; STF=Short-Term Funding; T1=Tier 1. Clustered standard errors (at the bank level) are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

4.9 Figures

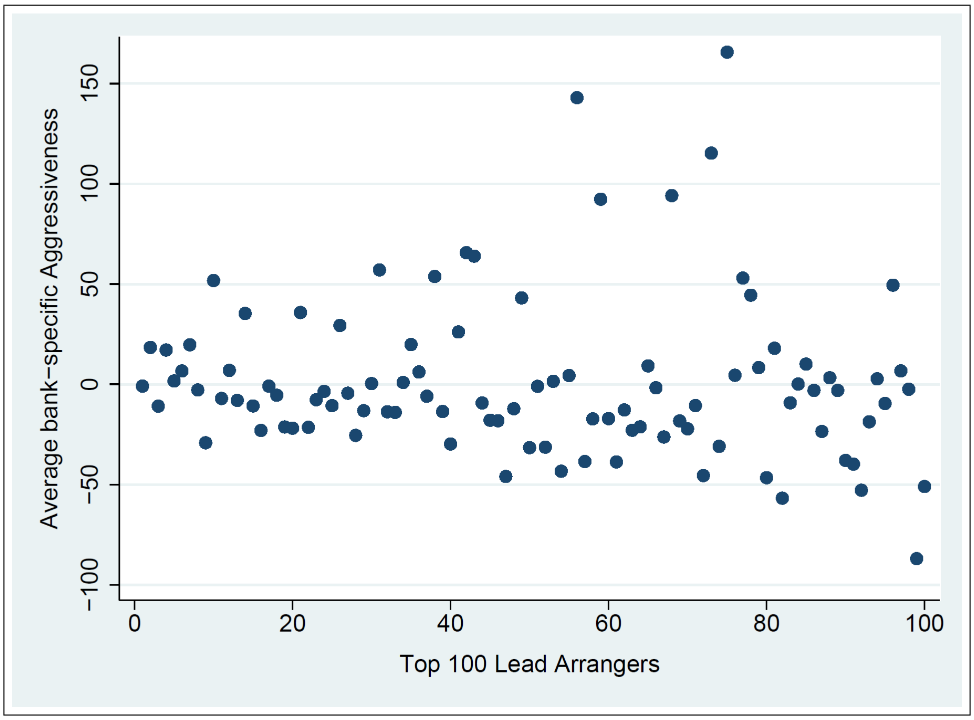

Figure 1: Average Aggressiveness of Top 100 Lead Arrangers

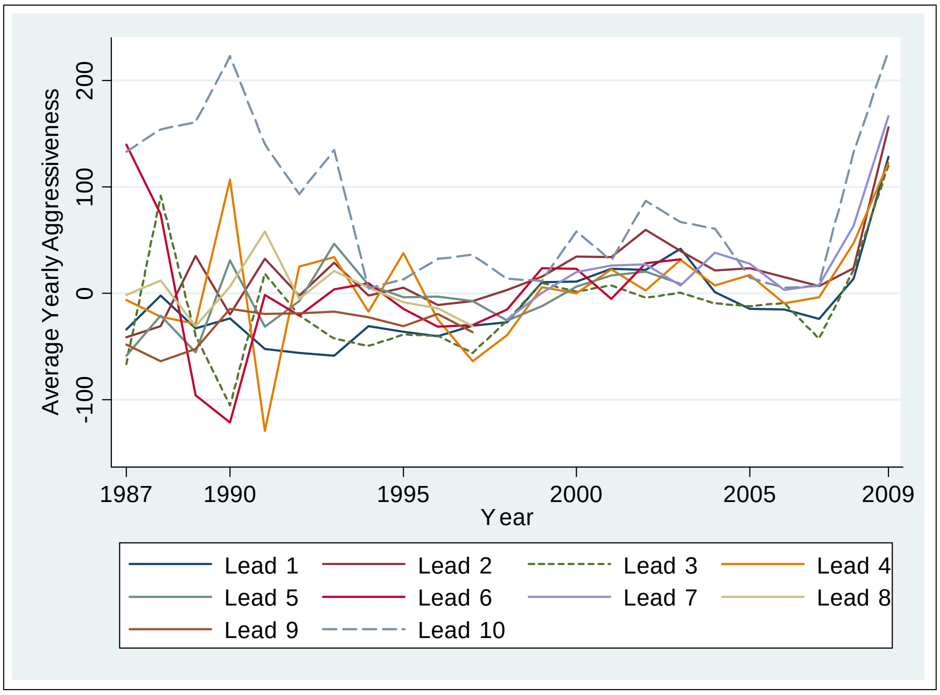

Figure 2: Average Yearly Aggressiveness of Top 10 Lead Arrangers

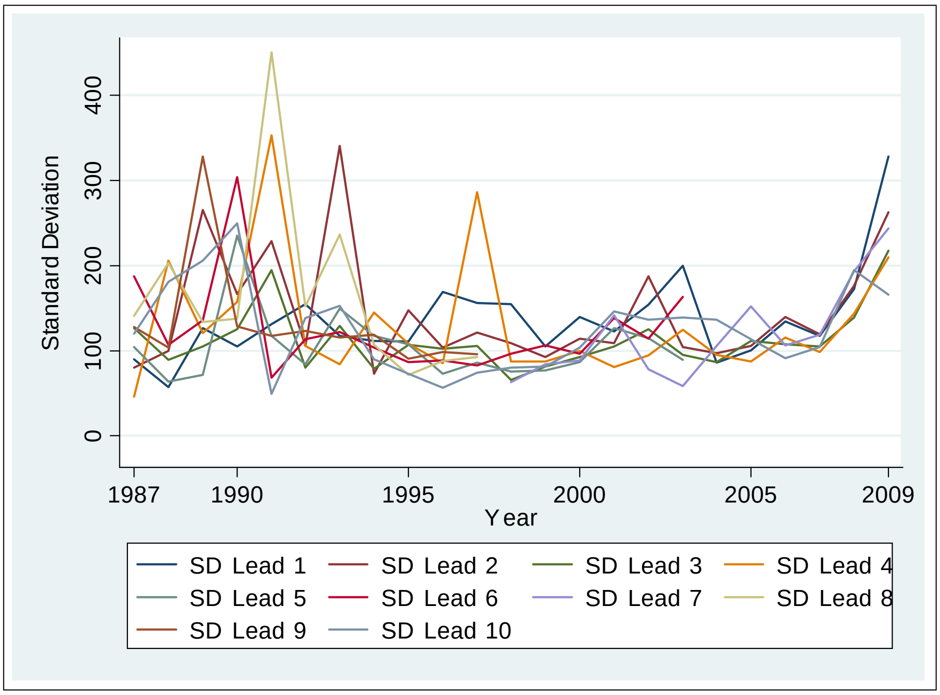

Figure 3: Standard Deviation of Yearly Aggressiveness of Top 10 Lead Arrangers

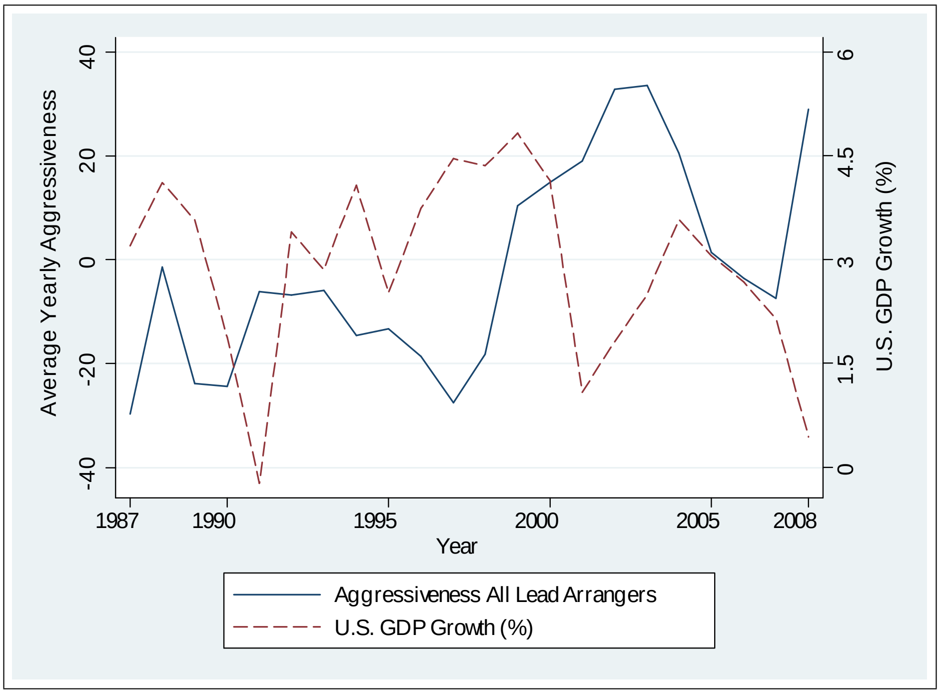

Figure 4: Average Yearly Aggressiveness of all Lead Arrangers and U.S. GDP Growth over Time

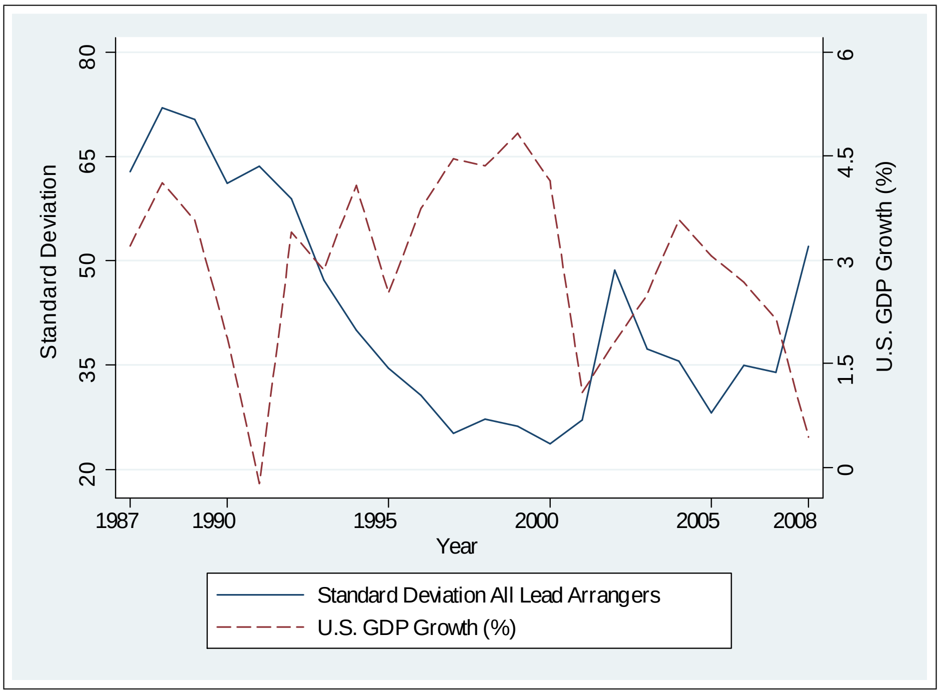

Figure 5: Standard Deviation of Yearly Aggressiveness of all Lead Arrangers and U.S. GDP Growth over Time

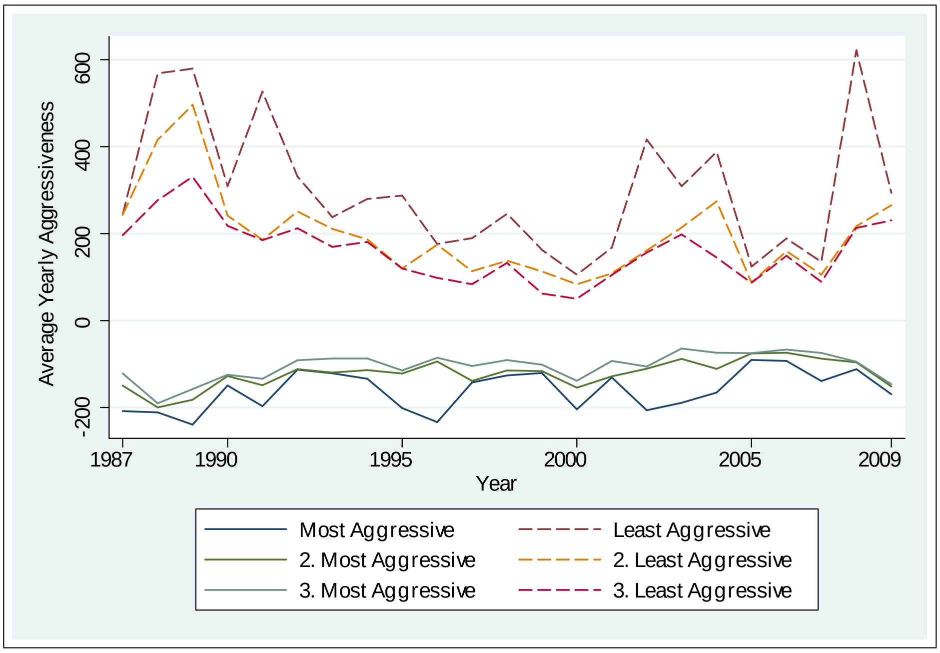

Figure 6: Yearly Aggressiveness of 3 Most and Least Aggressive Lead Arrangers over Time

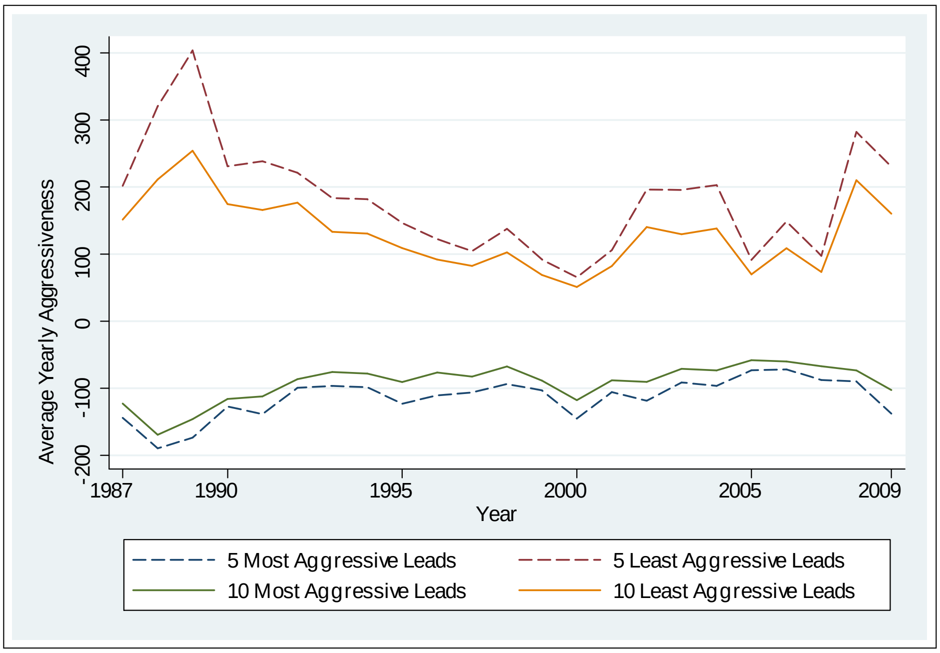

Figure 7: Average Yearly Aggressiveness of 5 and 10 Most and Least Aggressive Lead Arrangers over Time

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