Banking Beyond Bucks

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A thesis submitted for the degree of

Doctor of Philosophy at Maastricht University

November 7, 2019

This book was typeset using LaTeX.

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DISSERTATION

to obtain the degree of Doctor at Maastricht University,
by the authority of Prof. dr. Rianne M. Letschert, Rector Magnificus,
in accordance with the decision of the Board of Deans,
to be defended in public
on **Thursday, November 7th 2019**, at **14:00 hours**

by

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This research was financially supported by SWOL Professor's Fund.

Preface

The idea of giving thanks to everyone that has affected our lives, even if only briefly, is quite daunting. How could one ever thank everyone that has played a role, instrumental or not? How do we know how instrumental their role was? I approach this section with the ambition of brevity. My hope is that I show(ed) my gratitude and affection to those that were, and are, part of my life during our encounters.

That said, there a few people that I need to thank, because I know, without them, I would not be here. Stefanie, I hope I showed my gratitude to you throughout the years. However, I know I never specifically mentioned how much I admire and respect you. Your work ethic, your dedication, and ambition are admirable. We have not had the smoothest relationship, but then again, which supervisor-PhD relationship is? Yet, I find myself being thankful for those bumpy roads, because I believe you learn the true qualities of people in difficult times, and I can honestly say that you are a good role model to have. Rob, you were never really involved in my projects, yet you were always there. I am incredibly lucky I had you to push, help, and listen to me through many phases, like going to NYU. Thank you, for being the mediator, the brains behind funding, and a guide for me. Nadja, our relationship was short, yet instrumental. The first year was a forming year, and I wouldn't be where I am today if not for you. Thank you for the trust you had in me, from day one. Tony, you welcomed me in NYU and gave me so much of your time, thank you for teaching me so much in a such a short period of time. To the committee members, Prof. Dennis Bams, Dr. Annelies Renders, Prof. Peter Sampers, and Prof. Harald Sander, thank you for taking the time to read my dissertation and providing me with comments to improve it, my gratitude is immense.

Ladies, Carina, Cecile, Els and Francien, you are the center of gravity. I am now more aware than ever before, just how important you ladies really are. Thank you, not only for all the work you do, but also for being there, to chat, eat, and share recipes. Jaap, you took on many roles throughout the years, and I don't really know how to thank you for that, other than to say thank you, knowing it is not enough. Paulo, there are very few people that are as intelligent and as genuinely good as you, I know no other. Thank you for sharing that with me. Wiebke, you were often my sanity check. PhD-life would have been difficult without you, I am glad I didn't have to figure out just how difficult.

Mamita, Papito, Myriam, Sarya, thank you for not asking questions when you knew I did not want to answer any. And thank you for being my biggest fans always, even when there was no reason to be. Mi stima bosnan, albiyeti. Rogier, there is too much to say, I would not know where to start or where to end. You are my hero.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Banks fulfill an important role in the economy and in society by being one of the main providers of financing. However, these institutions do not enjoy a reputation for being free of scandals, or for being socially inclined. Especially following the 2008 financial crisis, society as whole was forced into realizing how important these institutions are indeed.

There are many forms of banks, and many forms of banking. The focus of this dissertation is on the syndicated loan market. The syndicated loan market caters mainly to very large loans, which individual banks are rarely, if ever, able to provide independently. A syndication is therefore, in essence, a pooling of different banks, and their funds. This pooling allows for greater availability of cash to fund single large projects and/or firms. There are many reasons for banks to engage in syndicated lending, such as knowledge transfer, risk sharing and bypassing regulation (Chowdhry and Nanda, 1996; Pichler and Wilhelm, 2001; Tykvová, 2007). For example, from a regulatory perspective syndication may result from the limit on loan size as a portion of a bank's equity capital. From a risk sharing perspective, it may reflect a bank's diversification strategy.

Syndicated lending represents the largest source of US corporate financing (Sufi, 2007). Worldwide, syndicated lending reached an 11-year high of approximately US$5.28 trillion in 2018, of which approximately 17% originated in Europe (Dealogic, 2019; European Commission, 2019; Reuters, 2018). To put it into perspective, the annual GDP of the Netherlands in 2017 equaled US$0.826 trillion.

A syndicate is organized differently from a bilateral loan. Syndicate members are categorized as either lead arrangers or participant lenders, with generally one lead arranger that acts as managing agent for the group. The lead arranger establishes a relationship with the borrower, and fulfills the role of information collector ex ante, and loan monitor ex post. Importantly, each bank that forms part of the syndicate is a direct lender to the borrower, evidenced by a separate note, although there is only one loan agreement contract. The lead arranger signs a preliminary agreement, called a mandate, with the borrower, specifying covenants, fees, collateral, loan amount and a range for the interest rate. The lead arranger then turns to potential participant lenders, with an information memorandum on the borrowing firm, which includes privately acquired information.

When banks agree to become participants in a syndicate, they sign the loan jointly with the lead arranger. Each participant holds a share of the loan, and the loan terms are identical for all members of the syndicate. The lead arranger traditionally receives a fee for loan management.

To date, the academic literature on syndicated lending has focused mostly on studying the effects of syndicate structure on information asymmetry, the effect of lead arrangers' reputation, loan pricing, and liquidity management. A distinguishing feature of the syndicated loan market is the information asymmetry within a syndicate. Participant banks are generally concerned about adverse selection and moral hazard. The former is when lead arrangers sell participant banks portions of bad loans, and the latter is when lead arrangers have less incentive to monitor the borrower once the loan has been signed.

Each of the chapters in this dissertation is related to specific issues that have been at the forefront of both the general media and recent academic literature. More specifically, they deal with hotly debated issues of Corporate Social Responsibility (Chapter 2), the usefulness and implications of Credit Rating Agencies (Chapter 3), and systemic risk (Chapter 4). The latter two have been at the forefront of financial policy debate since the financial crisis of 2008, while the former is becoming increasingly important in light of the severe threats of climate change.

Corporate Social Responsibility (CSR) and its pricing in financial markets has been studied in a number of influential papers. Goss and Roberts (2011) examine the link between corporate social responsibility (CSR) and bank debt and find that low quality borrowers with discretionary CSR spending face higher spreads and shorter maturities. Chava (2014) studies the effect of a firm's environmental profile on its cost of equity and debt capital and finds that firms with environmental concerns have higher spreads on their loans and fewer banks participate in their syndicate. Esty and Megginson (2003) investigate the effect of investor rights protection on the size and concentration of lending syndicates and find that lower legal enforcement mechanisms lead to larger and more diffuse syndicates. The chapter in this dissertation is most closely related to Hong and Kacperczyk (2009), who provide evidence that social norms are priced in the equity market. They show that sin stocks, stocks in the alcohol, tobacco, and gaming industry are held less by norm-constrained institutions and have a higher expected return relative to otherwise comparable firms.

In Chapter 2, "Do Banks Really Care? Evidence from the syndicated loan market", we contribute to this literature by investigating the effects of social norms in the syndicated loan market. We look at whether firms in the alcohol, tobacco and gaming industry have different loan prices relative to otherwise similar firms. There is common belief that social norms outweigh the pure profit motive at times. One example of norm-constrained behavior in financial markets is socially responsible investments (SRI). Two common SRI strategies in the equity market involve shunning sin firms, i.e. companies involved in the production of alcohol, tobacco, gaming, and favoring firms with high corporate social

responsibility (CSR) (Statman and Glushkov, 2009). We investigate if sin firms can obtain financing from banks relatively easily or whether social norms also affect bank lending decisions. If banks are indeed not norm-constrained, we expect sin firms to be able to obtain similar loan terms as comparable firms. If, however, sin firms are shunned in the bank loan market, we expect to observe a higher spread for these firms. Contrary to expectations, we find that spreads on loans to borrowers in sin industries are consistently and significantly lower than spreads on loans to otherwise comparable firms, even after controlling for general firm, loan, and bank factors known to affect the cost of debt.

Following the debate on the failure of credit rating agencies (CRAs) to adequately assess the risk inherent in complicated financial products, their value and effectiveness have been extensively researched. We focus on their role in the cost of capital setting. According to Becker and Milbourn (2011) issuers seek credit ratings to improve marketability, and importantly, pricing of their financial obligations. Investors, financial intermediaries, and regulators use ratings as an indicator of risk and likely repayment of securities, they disseminate information on default probabilities and limit duplication of risk in financial markets. Ratings are determining factors in regulations as a tool for measuring risk. Commercial banks, insurance companies and pension funds are among some of the financial institutions which are bound by regulations based on credit ratings. Thus, credit ratings are a key channel of information availability and are considered important by legislators, regulators, issuers, and investors alike. Boot, Milbourn, and Schmeits (2005) show that credit ratings serve as focal points, where they help fix the equilibrium in environments where multiple equilibria would otherwise exist. Faulkender and Petersen (2005) find that firms with publicly available credit ratings are able to raise more debt. Bosch and Steffen (2011) show that credit ratings provide a certification which is critical to the supply of debt financing. Our paper is most closely linked to Livingston and Zhou (2010) who find that split ratings, a proxy for uncertainty, is priced by bond holders.

Chapter 3 looks at the effects of borrower credit ratings on borrower loan spreads in the syndicated loan market. Loan interest rates are determined by the perceived riskiness of borrowers. Information on the riskiness is limited and difficult to obtain. This information scarcity, introduces uncertainty in the certification process of banks. Credit Rating Agencies (CRAs) are specialized information gatherers that evaluate the riskiness inherent to a country, corporation or specific debt instrument (Bavaria, 2002), and indeed, they play an increasingly important role in banks' risk assessment of potential borrowers. Correspondingly, their existence seems to reduce the information uncertainty greatly. However, CRAs have been criticized often due to the uncertainty in the rating determination process. One would think that the existence of multiple (independent) CRAs would serve as a remedy for this. This would indeed be true, when and if the letter ratings for a product are the same across rating agencies. However, when the CRAs independently assess the risk of borrowers, and they do not come to the same conclusion, resulting in what is often termed a 'split rating', the uncertainty becomes twofold. First,

the uncertainty of the risk that exists regardless, and second, the uncertainty about the true estimate of this risk. In such a scenario, the informativeness of the ratings is greatly decreased because it highlights the uncertainty around a borrower's credit worthiness.

We investigate this uncertainty in the syndicated bank loan market. We argue that when banks are uncertain about the credit worthiness of a borrower, they will only be willing to provide capital at a higher rate. We call this the 'split premium.' Results show that borrowers experience increased loan spreads when their ratings are changed from two equal ratings to split ratings. Similarly, borrowers whose ratings change from split to two equal ratings experience a discount. We also show that the split premium is increasing in the size of the split, i.e. the level of uncertainty. On average, split rated borrowers have approximately 5% higher spreads than non-split rated borrowers, which amounts to approximately a quarter of a million dollars per year in additional interest payments for a typical loan.

The global financial crisis showed that the connections between banks can have dire consequences on the system with large costs to society. Banks are linked through many channels, some of the most distinguished being the interbank deposit market, deposit interest rate risk, and syndicated loans. Syndicated lending carries many positive elements, mainly related to diversification effects. In an effort to reduce the apparent risk of the loan portfolio, syndication has become increasingly important, disregarding potential negative effects. Ibragimov, Jaffee, and Walden (2011) show theoretically that diversification efforts by individual banks may be optimal for them, but may prove sub optimal for society. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) show that diversification is mostly beneficial for small shocks, however, if a shock is large enough a highly diversified lending pattern can create a more fragile system.

Chapter 4 aims to measure to what extent financial markets see the increased interconnectedness of banks, created by their syndicated lending activity, as a threat to financial stability. This chapter is most closely related to Cai, Eidam, Saunders, and Steffen (2018), who were the first to explicitly empirically measure the interconnectedness of banks resulting from syndicated loans. Their results show that a higher interconnectedness in the syndicated loan market is positively correlated with, but distinct from, other known measures of systemic risk.

Chapter 4 uses their measure to test whether markets recognize the systemic connections that arise from syndicated loans. Specifically, we look at whether the equity and Credit Default Swaps (CDS) markets recognize the interconnection between banks stemming from the syndicated loan market. The CDS market revolves around instruments that are a bet on the default of the underlying firm. Therefore it is perfectly suited to investigate this question, as it reflects the market's downside sentiment. The loan sharing, stemming from syndication, results in banks holding very similar portfolios, which is good in normal times, but is risky in bad times. We show that equity markets react almost instantly to the signing of a new syndicated loan that greatly increases the

interconnectedness of the associated banks.

Interestingly, our results show that the global financial crisis shook investors into recognizing these risks. Before the failure of Lehman Brothers, a large investment bank, financial markets did not appear to price the systemic risk inherent in syndicated loans. Since its demise in September 2008, markets appear to more closely follow the interconnectedness in the financial system, and react accordingly. However, we find that markets only react to the announcement of deals that have a large negative impact on the degree of interconnectedness. The economic and statistical significance of the result is driven by the 5% of deals that lead to the largest increase in interconnectedness. There is no such impact in the middle or the left-tail of the distribution, suggesting that most syndicated loans are treated as day-to-day business, and that equity markets mainly care about the potential downside risk of such deals. Overall, the chapter shows that market participants are concerned about the underexposed negative implications of syndication. Risk is not appropriately diversified if it is spread across a small group of highly influential and large financial institutions, and this is recognized by the market.

Overall, this thesis sheds light on the impact of the syndicated loan market on the economy as a whole. We highlight their social impact, as well as their role in providing stability through risk assessment, and fostering instability through their sheer magnitude.

Chapter 2

Do Banks Really Care? Social Norms in Bank Lending*

2.1 Introduction

There is common belief that social norms outweigh the pure profit motive at times. One example of norm-constrained behavior in financial markets is socially responsible investments (SRI). Two common SRI strategies in the equity market involve shunning sin firms, i.e. companies involved in the production of alcohol, tobacco, gaming, and favoring firms with high corporate social responsibility (CSR) (Statman and Glushkov, 2009). Hong and Kacperczyk (2009) show that sin firms are shunned by norm-constrained institutions, such as banks, insurance companies, university endowments, and pension funds. Because of the neglect effect (Merton, 1987), sin firms trade at 15-20% lower valuations and outperform comparable stocks by about 2.5% per year. Because sin firms are shunned in equity markets, Hong and Kacperczyk (2009) suggest that they move to the less transparent debt markets to obtain financing. They find that sin firms have about 20% higher leverage ratios than other firms.

Building on the evidence in Hong and Kacperczyk (2009), we investigate if sin firms can obtain financing from banks relatively easily or whether social norms also affect bank lending decisions. If banks are indeed not norm-constrained in the less transparent debt markets, we expect that sin firms are able to obtain similar loan terms as comparable firms. If, however, sin firms are also being shunned in the (less transparent) bank loan market, these firms should pay a higher spread. Understanding the role of social norms in bank lending is interesting, because bank debt is a predominant source of new external funds for US corporations (Chava (2014); Shrieves and Dahl (1992)). Lee and Mullineaux (2004) state that the syndicated loan market has become the largest source of firm financing worldwide.

We focus our investigation on the effects of social norms in the bank debt market by

*This chapter is co-authored with Nadja Guenster (University of Muenster), Stefanie Kleimeier (Maastricht University, University of Stellenbosch Business School and Open University)

looking at the three industries identified by Hong and Kacperczyk (2009) and collectively known as the "Triumvirate of Sin", namely alcohol, tobacco, and gaming. We compare the spreads on the loans of sin firms to the spreads on the loans of comparable firms. The bank loan data are taken from DealScan and cover the years 1987 to 2012. We start with a sample of approximately 85,000 loan observations for private and public firms. However, our sample decreases to about 6000 loans to public firms when we merge our loan information from DealScan with the borrower's financial information from Compustat.

Contrary to our expectations, we consistently find that sin firms pay an economically relevant and statistically significant *lower* spread than otherwise comparable firms. Considering loans to public and private firms and controlling for loan characteristics, the spread paid by sin firms is between 18.85 bps and 32.06 bps lower than the spread paid by comparable firms. After controlling for firm characteristics, this difference widens and public sin firms pay between 42.71 to 57.2 bps less than comparable public firms. As the overall average spread for our sample is about 283.2 bps, these findings imply that sin firms have a 10-20% lower cost of bank debt relative to otherwise similar firms.

We investigate four possible explanations for these findings. First, Kim, Park, and Wier (2012) show that the financial reporting quality of sin firms is superior relative to comparable firms. Sin firms have a higher predictability of earnings for future cash flows and a more timely recognition of losses. To investigate if the more favorable loan terms for sin firms could be due to the better accounting quality, we include measures for accrual quality. As expected, accrual quality has a significantly negative effect on the cost of bank debt. However, even after controlling for accrual quality, the negative sin effect persists. Second, we investigate if the lower spread paid by sin firms can be explained by relationship lending. Relationship lending involves the acquisition of customer-specific information as a result of multiple interactions over time, which decreases information asymmetry (Boot, 2000). Lower information asymmetry could lead to lower spreads (Bharath, Dahiya, Saunders, and Srinivasan, 2011). In line with this reasoning, our results show that relationship lending indeed lowers the spread. Again, however, the sin coefficient remains statistically significant and similar in magnitude. Third, we investigate whether loans to sin firms serve as a hedge for banks due to the anti-cyclical nature of their business. To measure this effect, we estimate a CAPM-beta for each firm and include it in our model. Beta is significantly positively related to the spread, but the sin coefficient is not affected by the inclusion of betas. Finally, we investigate whether organizational structure could be driving our results. We include a measure for corporate diversification following Aivazian, Qiu, and Rahaman (2015), whose results show that diversified firms have significantly lower loan rates than comparable focused firms. Similar to their results, we find that diversification is negatively related to loan spreads, however, this does not affect the spread for sin firms. As such, accrual quality, relationship lending, cyclicality, and corporate diversification do not explain our results. The lower spreads paid by sin firms remain a puzzle.

2.2 Literature Review

Social scientists such as Akerlof (1980) and Becker (1957), propose that agents obey social norms unless there is a financial gain in violating the norm. Akerlof (1980) argues that social norms established and followed by a majority in a community will persist despite carrying a cost, because agents fear a loss of reputation and utility. This in turn implies that the violation of a norm by agents that are less norm-constrained will result in a gain to those respective agents. Hong and Kacperczyk (2009) were the first to empirically show that these theories translate to investors' preferences in the stock market. They investigate the pricing of sin stocks, i.e. publicly traded firms in the alcohol, tobacco, and gaming industry. Their results show that sin stocks have higher expected returns than otherwise comparable stocks. They further corroborate the link to the agency theory above by observing lower ownership levels by norm-constrained institutions, such as (public) pension funds or universities.

Kumar and Page (2014) also investigate the effects of social norms on investor behavior. The authors test the hypothesis that sophisticated individuals deviate from established norms only when they perceive the benefits of deviating are large. Consistently, their results show that when gambling-averse institutions invest in lottery-type stocks, these investments generate strong abnormal returns. Correspondingly, sin-averse institutions earn higher abnormal returns on those sin stocks they choose to hold. Thus, both Kumar and Page (2014) and Hong and Kacperczyk (2009) find that social norms lead to higher abnormal returns for shunned firms in the equity market.

Fauver and McDonald (2014) investigate whether heterogeneity in social attitudes impact equity markets. The authors develop a measure of time varying social norms pertaining to sin stocks in the G20 nations and report that while sin stocks are shunned in some nations, they are not shunned in others. Thus, sin firms in countries where society is opposed to the products or services, experience decreased valuation relative to non-sin firms. Similarly, countries where these industries are not shunned by societal views do not experience valuation differences with otherwise similar firms. The authors conclude that there is a significant relation between social views and equity market valuation of firms that do not comply with these views, consistent with the conclusion drawn in Hong and Kacperczyk (2009) that sin firms have lower equity valuations because society shuns these stocks in the equity market.

The shunning that sin firms experience does not seem to be limited to equity markets. Novak and Bilinski (2014) provide evidence of sin shunning in the labor market. Their results show that executives in the alcohol, tobacco, and gambling industries earn a significant compensation premium, which compensates the executives for the social stigma related to employment in sin industries. Consistent with these findings, they document that executive compensation in sin industries is higher in periods, and in states, with higher social aversion to sin and that the executives hold less outside board seats, indicating lower social prestige. Taken the together, the evidence suggests that executives

demand a compensation premium for bearing the negative costs of working in industries perceived negatively.

Leventis, Hasan, and Dedoulis (2013) provide evidence of social norms in audit pricing. Their results show that firms charge significantly higher audit and consulting fees to companies that deviate from prevailing social norms. They also show that audit pricing levels within the "sin" group, which include companies in the alcohol, tobacco, firearms, gambling, and nuclear power industries, depend both on prevailing political views and on the level of "vice" exhibited by sin companies.

In addition to the sin effect in equity markets, Hong and Kacperczyk (2009) also give some insight into the capital structure of sin firms. Next to showing that the equity of sin stocks is undervalued, making it more expensive for these firms to finance operations using equity, the authors postulate that sin firms use debt to finance their operations. Their results show that sin firms have 19.3% higher leverage ratio than the typical company, providing support for this expectation. One explanation for the observed leverage ratio is that debt markets are less transparent than equity markets, leading to potentially advantageous conditions for sin firms. Although it is possible to trace large public issuances of corporate bonds, large amounts of bank debt are difficult to trace (Hong and Kacperczyk, 2009), making bank debt particularly interesting to study in this setting. In this paper, we analyze, if sin firms are also shunned in debt markets, specifically focusing on the syndicated bank loan market.

While the empirical evidence suggests that social norms affect equity investment decisions and equilibrium prices, we know little about the effect of social norms in corporate debt markets. Based on the findings in the literature to date, we expect that sin firms have to pay a higher yield or, at best, there is no difference in the yield relative to otherwise similar firms. Existing evidence on social norms in the bank debt market is limited to studies looking at a broader definition of social norms. Goss and Roberts (2011) analyze the effect of firms' corporate social responsibility standards on the cost of bank loans. They include the KLD screens on nuclear, military, tobacco, gambling, and alcohol in some regressions as control variables. However, the focus of their study is to show that lenders demand higher yield spreads from borrowers with the worst records in social responsibility based on the KLD strengths and concerns indicators. Similarly, Chava (2014) shows a higher cost of debt and equity for firms with environmental concerns. Kim, Surroca, and Tribó (2014) show that borrowers' ethical behavior leads lending banks to charge lower interest rates. These low rates are further enhanced when borrowers and lenders exhibit similarities in their ethical guidelines, emphasizing the relationship aspect of bank lending.

2.3 Data and Method

In our empirical analysis, we focus on bank loans raised by US borrowers with loan data obtained from LPC's DealScan database. Our full sample consists of 86,514 loans to private as well as public borrowers signed between 1987 and 2012. DealScan provides an expansive list of loan characteristics as well as syndicate information, but data on borrower characteristics are limited to borrower name, industry, credit ratings and sales. We therefore also consider a sub-sample of 6,093 loans to public borrowers for which we collect detailed borrower characteristics from Compustat. In order to match DealScan to Compustat, we use the matched dataset provided by Roberts and Chava (2008). Analyzing both samples allows us to, on the one hand, examine the largest possible cross-section, and on the other hand, include an array of factors known to affect loan terms. The full sample allows for the analysis of a large, comprehensive sample of loans in which we consider the main drivers of loans spreads, e.g. credit risk and loan characteristics. The Compustat sample allows us to consider the impact of specific borrower characteristics on loan spreads, albeit on a limited number of loans to public borrowers only. Our main question is centered on the cost of bank debt for sin firms in comparison to other, non-sin borrowers. We therefore estimate the multivariate regression model shown in Equation (2.1). Our estimates are OLS estimates with standard errors clustered by borrower.

$$Spread_i = \alpha + \beta_1 Sin_i + \beta_2 Comparable_i + \beta_3 Controls_i + \epsilon_i, \tag{2.1}$$

where $Spread_i$ represents the cost of debt of loan i, Sin_i identifies whether the loan is made to a borrower in a sin industry, $Comparable_i$ identifies an industry control, $Controls$ is a vector of firm, loan, or bank characteristics and ϵ_i are the residuals. The dependent variable $Spread_i$ measures loan i's all-in-spread drawn (AISD) as the total annual cost net of upfront fees for each dollar used under the loan commitment (Ivashina, 2009). The AISD is measured in bps. over LIBOR or LIBOR equivalent [1]. Sin is a dummy variable defined to take unity if loan i is made to a sin firm and zero otherwise. We adopt Hong and Kacperczyk (2009)'s definition of sin, which includes all borrowers in the alcohol, tobacco, and gambling industries, labeled "Triumvirate of sin". We use the SIC codes provided in DealScan to identify the industry group each borrower belongs to. We group borrowers based on the Fama and French (1997) industry classification. Firms in the Fama-French industry group 4 with SIC codes 2080 - 2085 belong to the Beer & Liquor group and firms in industry group 5 with SIC codes 2100 - 2199 belong to Tobacco Products, and both groups are classified as sin stocks. The Fama-French classification scheme does not differentiate the gaming industry from the hotel industry or other entertainment firms. Therefore, the NAICS classification is used instead, which identifies gaming stocks as those pertaining to the following NAICS codes: 7132, 71312, 713210, 713290, 72112, 721120. The NAICS codes are obtained through matching with Compustat, thus this method can

[1] AISD is winsorized at the 1% level.

only be applied to the Compustat sample. For the DealScan sample, we manually identify firms in the gaming industry using the 4-digit SIC codes.

In order to control for the fact that some companies - which are not flagged or identified as sin stocks in the first phase - have segments that operate in sin industries, a second company screening is applied. We start with the Hong and Kacperczyk (2009) augmented list of sin companies which utilizes Compustat segments data from 1985 to 2006. We expand this list by applying the same method to the data for the remainder of our sample period, i.e. 2007 to 2012. Thus, a borrower is identified as a sin firm if any of its segments has an SIC code in the Fama and French industry group 4 or 5 or a NAICS code in the gaming group, as previously defined. Hong and Kacperczyk (2009) argue that this second screening process is imperative in obtaining an accurate list of sin firms, since many companies have diversified operations.

While in their paper, Hong and Kacperczyk (2009) focus on the Triumvirate of sin, two other industries could be considered sinful. The first one is the sex industry. In line with Hong and Kacperczyk (2009) we decide against the inclusion of this industry due to the limited number of publicly traded companies and the lack of an industry identifier even at the NAICS level. The second, potentially sin-related industry is defense. However, due to the uncertainty in whether, and when, the American population started to perceive the defense industry as sinful, it is problematic to classify it as such.

Including a sin dummy in Equation 1 allows us to measure whether sin firms have a different loan spread relative to otherwise similar firms, while controlling for other borrower, loan, and/or bank characteristics. However, we acknowledge that our control variables might not be complete and we are particularly concerned about unexplained industry-effects. In order to maintain a parsimonious specification, we construct a comparable industry dummy following Hong and Kacperczyk (2009). We consider Fama and French (1997) industry group 2 (food) and 3 (soda) and 43 (meals, restaurants, hotels, and motels) to be such comparable industries. Note that our comparable industry dummy takes the value of one in two instances, first if the loan is to a sin firm and second if the loan is to a non-sin firm in one of the above mentioned Fama and French comparable industry groups.

We include sin in the comparables indicator variable, which allows for an immediate test of significance, next to an easy-to-interpret coefficient. Any comparable firm will have β_2 mean spread in bp. A sin firm on the other hand will have $\beta_1 + \beta_2$ on average. This means that the difference between sin, and all comparable firms equals $(\beta_1+\beta_2)-\beta_2 = \beta_1$. Significance of this coefficient can therefore be interpreted as a significantly different average spread, or a 'mean shift'/'level shift' for sin firms, compared to their direct peers. Significance means that there is indeed a sin effect, controlling for other factors including industry. In short, the comparable dummy is an industry control variable, which still allows for a parsimonious specification.

Following existing literature, we control for firm financial characteristics, loan char-

acteristics and bank characteristics in the following manner. We start by controlling for firm credit ratings. Credit ratings are widely thought to be the main driving force in determining loan terms. We use the Moody's senior debt rating, available in DealScan as the main rating. In addition to ratings, we control for firm size. We have two proxies for firm size, one obtained using DealScan data and one obtained using Compustat data [2]. Firm size in DealScan is computed as the natural logarithm of firm sales. Our Compustat measure for size is proxied by the natural logarithm of a firm's total assets (Sufi, 2007). The theory is that larger firms have a greater ability to withstand negative shocks to cash flows and are thus less likely to default. Larger firms are also more likely to be viewed as less risky by banks and should experience a lower cost of debt (Goss and Roberts, 2011). The tangibility of firms is an important aspect in the pricing of bank debt, because lenders recover from risk exposure via tangible assets in case of default. We measure tangibility as property, plants, and equipment, divided by total assets. Leverage has been shown to lead to higher spreads. Leverage is measured as total debt to total assets (Demerjian, 2011). Profitability of firms is also expected to be an important determinant of cost of debt [3]. Here we define profitability as EBITDA divided by total assets. One of the most important determinants of bank loan terms is the default probability of the borrowers. Although the ratings are the primary measure of default probability, we follow Chava (2014) in also measuring the modified Altman Z-score of each borrower. We use the modified Z-score because it allows us to control for leverage separately. Given the nature of our research, leverage is a key component as it is one of the main driving elements in loan pricing. We calculate the modified Z-score in the following way:

$$\frac{1.2 \times \text{Working Cap.} + 1.48 \times \text{Retained Earnings} + 3.3 \times \text{EBIT} + 0.999 \times \text{Sales}}{\text{Total Assets}}. \tag{2.2}$$

A higher Z-score means firms are farther from financial distress. All else equal evidence shows that higher leverage, lower profitability, and a lower Z-score are related to higher default risk, and in turn, a higher cost of debt. Following Fauver and McDonald (2014) we also control for the growth options of firms. All else equal, a firm with better growth opportunities should face lower default risk and thus enjoy lower loan prices. Fauver and McDonald (2014)'s results suggest that sin firms have higher growth opportunities. Specifically, they find that sin firms have higher free cash flows to assets and higher capital expenditures-to-sales ratios.

In addition to controlling for firm characteristics, we also control for the heterogeneity in loans. We include several loan features which have been found to affect loan terms. We start by controlling for loan size, measured as the natural logarithm of loan size in

[2]We perform a sanity check on the reliability of the borrower size variable obtained from DealScan, by cross-validating it with the borrower size variable obtained from Compustat. In particular, we drop a small number of observations that deviate abnormally from a linear relationship ($R^2 = 0.7$) between the two size proxies.

[3]Tangibility and Profitability are winsorzied at the 5% level.

Table 2.1: Descriptive Statistics

This table presents summary statistics for variables from both DealScan and Compustat. The variables are presented for the maximum number of observations, where the dependent variable is not missing.

	Sin			Comparable			Non-Sin			Difference of means	
	N	Mean	SD	N	Mean	SD	N	Mean	SD	sin - comparable	sin - non-sin
Firm Characteristics											
Spread	1,095	265.4	215.5	8,227	288.7	226.4	85,419	283.4	222.1	-23.30***	-18.00***
Size	243	7.488	1.492	1,036	7.474	1.648	10,873	7.563	1.688	0.014	-0.075
Tangibility	243	0.615	0.346	1,027	0.684	0.348	10,827	0.618	0.414	-0.069***	-0.003
Leverage	235	0.616	0.209	1,012	0.571	0.218	10,505	0.540	0.228	0.045	0.076
Profitability	243	0.147	0.058	1,027	0.155	0.080	10,846	0.133	0.094	-0.008**	0.014
Z-Score	235	1.494	0.836	965	1.838	1.134	10,006	1.644	1.361	-0.344***	-0.150***
CAPX/Sales	241	0.109	0.116	1,019	0.0878	0.122	10,795	0.203	12.33	0.021	-0.094
Earnings Quality	232	-0.019	0.012	1,070	-0.0189	0.015	10,554	-0.024	0.021	0.000	-0.004***
Earnings Persistence	246	0.332	0.292	1,144	0.373	0.339	11,800	0.335	0.421	-0.041**	-0.003
Earnings Predictability	246	2.067	1.917	1,144	9.678	186.8	11,800	14.30	338.4	-7.611*	-12.233***
Beta	213	0.977	0.560	737	0.915	1.633	7,569	0.994	1.343	0.062	-0.017
FCF/Assets	243	-0.037	0.162	1,022	-0.0201	0.159	10,772	-0.035	0.183	-0.017*	-0.002
Termloam	1,095	0.345	0.476	8,227	0.345	0.475	85,419	0.326	0.469	0.000	0.019
Borrowersales (Million)	748	3,678	12,203	6,040	2,486	6,785	61,277	2,250	10,305	1192	1428
Borrowersales (log)	748	20.21	1.837	6,040	19.91	1.94	61,271	19.67	1.912	0.300	0.540
Loan Characteristics											
Maturity	1,049	51.68	23.13	7,705	51.47	24.38	79,508	49.28	25.05	0.210	2.400
Loansize (Million)	1,095	358.7	938	8,227	246.1	621.8	85,419	195.9	523.1	112.6	162.8
Loansize (log)	1,095	18.45	1.613	8,227	18.02	1.7	85,419	17.83	1.694	0.430	0.620
Senior	1,091	0.992	0.091	8,201	0.99	0.0977	85,154	0.993	0.084	0.002	-0.001
Secured	524	0.748	0.435	4,320	0.826	0.379	46,589	0.83	0.376	-0.078***	-0.082***
Covenant	1,095	0.342	0.475	8,227	0.328	0.47	85,419	0.333	0.471	0.014	0.009
Bank Characteristics											
Relationship number	1,095	0.111	0.194	8,227	0.0959	0.183	85,394	0.090	0.179	0.015	0.021
Relationship Dummy	1,095	0.262	0.44	8,227	0.232	0.422	85,394	0.218	0.413	0.030	0.044

US dollars, following Sufi (2007). Another important aspect of loans is the maturity. Loan maturity is measured as the natural logarithm of the number of months between loan inception and loan end-date (Chava, 2014; Hasan, Park, and Wu, 2012). There are two differing views on the effects of maturity on cost of debt. The "trade-off" hypothesis posits that banks will charge higher spreads on loans with longer maturities to account for the risks involved in lending over longer periods of time. The "credit-quality" hypothesis argues that long-term debt should have lower cost of debt because high-risk lenders are excluded from this type of debt (Goss and Roberts, 2011). Thus, the effect of maturity is an empirical question. We also include dummy variables to control for whether the loan is secured, whether there are financial covenants in place, for the exact purpose of the loan, and we control for the type of loan by capturing whether it is a term loan or any other type of loan.

Lastly, we control for bank characteristics. Although the main drivers of loan terms are borrower characteristics, there is undoubtedly an interaction between bank preferences and the loan terms borrowers receive. Given that we are mainly interested in whether banks are socially responsible entities, and whether this affects their lending decisions, we control for whether banks are signatories of the Equator Principles. This follows from the premise that these banks might generally be norm-constrained, as they make an explicit social association by joining the equator principles. We identify whether any of the lead arrangers for a loan are signatories to the Equator Principles. Our hypothesis here is that lead arrangers that are Equator Principles Signatories will shun sin firms, and this will affect the loan terms these borrowers receive by the syndicate.

2.4 Results

In this section we discuss the results of the empirical analysis. We start with discussing the full DealScan sample including loans to private and public borrowers and continue with a discussion of the Compustat sample of loans to public borrowers only. The regressions include firm-level control variables and loan-level control variables, with standard errors clustered at the borrower level. The dependent variable is the loan spread in each regression, and the focus is on the sin coefficient. Table 2.1 presents the summary statistics for the Compustat and DealScan variables, for each respective sample, where we present the descriptives for the maximum number of available observations where spread is also available. The mean is presented for sin firms, comparable firms, and non-sin firms. This allows us to draw an inference, at an early stage, of the dynamics between these groups. As Table 2.1 shows, the loan spread is significantly lower for sin firms than for both comparable firms and all non-sin firms. The Z-score of sin firms is also significantly lower than that of both comparable firms and all non-sin firms. Although the magnitude of the difference is not alarming, it means that sin firms have higher credit risk than other firms. Interestingly, Table 2.1 also shows that loans to sin firms require, on average, less collat-

eral as the secured variable shows. This is significantly lower for sin firms than for both the comparable group and all other firms. The magnitude of the difference is negligible however. Overall, the descriptive statistics show that sin firms have lower spreads when compared to other firms, however, a majority of the firm and loan level characteristics are not statistically different between these groups.

Table 2.1 shows the results for different specifications on the full DealScan sample. Following Carey and Nini (2007) we use ratings as our primary measure of credit quality, as this is arguably the most important determining factor in loan pricing. Regression 1 of Table 2.2 presents the specification controlling only for credit quality measured by credit rating. The sin coefficient for this specification is negative and significant at the 5% level, largely in line with the descriptive statistics. Regression 2 shows a more comprehensive specification, which controls for a multitude of loan-level characteristics. Adding loan-level characteristics decreases the sample size by approximately half, however, the sin coefficient remains negative at the 10% significance level. Controlling for borrower-characteristics represents a challenge when using only DealScan data. Borrower sales is reported, but a significant portion of observations is missing. Regression 3 includes borrower sales for robustness, and the sin coefficient remains negative, at -32 bps., and significant at the 1%-level. Due to the large decrease in number of observations stemming solely from this variable, we decide to exclude it from further specifications, as it does not materially affect results, but does significantly decrease the sample size.

One important factor that could lead to banks making lending decisions based on social norms are the Equator Principles. Although the Principles are specific to project finance, banks make an implicit association with social behavior, and thus, might treat sin firms differently than otherwise similar firms. In an effort to test this hypothesis, we control for whether banks are committed to the Equator Principles. Also, following from the premise that these banks are more likely to shun sin firms based on their social affiliation, we construct an interaction term between Equator Principles committed banks and sin firms. Regression 4 shows the specification controlling for Equator Principles committed banks, and it shows that while these banks charge lower spreads on average, they do shun sin firms, as evidenced by the fact that the overall sin effect remains negative, and statistically significant.

In an effort to control for firm level characteristics in a comprehensive manner, we match the loans in DealScan to firm financial data from Compustat. Table 2.3 presents the results for this sample. Note that the sample size decreases significantly in the matching process. However, this step is essential as it allows us to control for numerous firm level characteristics known to affect loan terms. In regression 1 we include all loan level characteristics as shown in regression 2 of Table 2.2 in addition to different firm level characteristics, such as firm size, leverage ratio, and Z-score. The results remain qualitatively similar to those shown in Table 2.2. After controlling for numerous loan level and firm level characteristics, the sin coefficient remains negative and significant at the

Table 2.2: Full DealScan Sample

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for the full DealScan sample. In this sample, firm characteristics are limited to credit ratings and borrower sales. Our main variable of interest is the sin dummy variable (Sin). In order to maintain a parsimonious specification, while still controlling for industry effects, we include a comparable industry dummy (Comparable). The Comparable dummy variable takes unity for firms in comparable industries, i.e. industry group 2 (food) and 3 (soda) and 43 (meals, restaurants, hotels, and motels), and when firms are sin firms. This allows for an immediate test of differences between sin firms and firms in comparable industries. Any comparable firm will have β_2 mean spread in bp. A sin firm on the other hand will have $\beta_1 + \beta_2$ on average. This means that the difference between sin, and all comparable firms equals $(\beta_1 + \beta_2) - \beta_2 = \beta_1$. We control for loan characteristics following existing literature. Lastly, we control for whether banks are equator banks. Banks make an explicit social association by joining the equator principles, allowing for the assumption that these banks shun socially irresponsible products and/or the producing firm. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Sin	-18.73*	-20.67**	-33.02***	-38.79***
	(9.776)	(9.845)	(10.09)	(12.02)
Comparable	5.194	15.33***	17.99***	19.23***
	(4.369)	(4.732)	(5.138)	(5.156)
Size			-4.949***	-4.587***
			(1.208)	(1.209)
Loan Characteristics				
Secured		60.40***	59.38***	58.18***
		(3.898)	(4.140)	(4.144)
Financial Covenant		-74.47***	-72.39***	-72.19***
		(3.064)	(3.553)	(3.545)
Termloan		65.92***	58.91***	58.75***
		(2.561)	(2.825)	(2.817)
Senior		-545.4***	-552.4***	-549.8***
		(21.97)	(24.16)	(24.09)
Loansize		-32.51***	-28.75***	-27.79***
		(0.820)	(1.233)	(1.225)
Multiple Tranches		-13.49***	-10.40***	-9.775***
		(2.558)	(2.751)	(2.749)
Currency		26.30	31.19	29.46
		(27.79)	(22.23)	(22.22)
Maturity		8.132***	8.025***	7.905***
		(2.223)	(2.503)	(2.484)
Bank Characteristics				
Equator Bank				-27.13***
				(2.393)
Equator Bank × Sin				18.56
				(19.37)
Constant	305.0***	1,308***	1,308***	1,286***
	(0.00173)	(38.14)	(36.16)	(36.26)
Observations	86,513	45,423	37,310	37,310
Adjusted R-squared	0.117	0.285	0.293	0.295
Rating Dummies	Yes	Yes	Yes	Yes
Purpose	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

Table 2.3: Compustat Sample

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for the matched DealScan-Compustat sample. This sample includes a wide array of firm-level control variables. Our main variable of interest is the sin dummy variable (Sin). In order to maintain a parsimonious specification, while still controlling for industry effects, we include a comparable industry dummy (Comparable). The Comparable dummy variable takes unity for firms in comparable industries, i.e. industry group 2 (food) and 3 (soda) and 43 (meals, restaurants, hotels, and motels), and when firms are sin firms. This allows for an immediate test of differences between sin firms and firms in comparable industries. Any comparable firm will have β_2 mean spread in bp. A sin firm on the other hand will have $\beta_1 + \beta_2$ on average. This means that the difference between sin, and all comparable firms equals $(\beta_1 + \beta_2) - \beta_2 = \beta_1$. We control for different firm level characteristics known to affect loan spreads. We also control for loan characteristics following existing literature. Lastly, we control for whether banks are equator banks. Banks make an explicit social association by joining the equator principles, allowing for the assumption that these banks shun socially irresponsible products and/or the producing firm. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
Borrower Characteristics		
Sin	-39.88*	-57.07**
	(21.08)	(23.15)
Comparable	26.79	27.78
	(20.93)	(21.18)
Size	10.34**	10.58**
	(5.208)	(5.231)
Tangibility	13.08*	12.71*
	(6.836)	(6.803)
Leverage	99.78***	100.1***
	(16.38)	(16.42)
Z - Score	-9.223**	-9.200**
	(4.139)	(4.136)
Profitability	-194.0***	-192.4***
	(42.57)	(42.68)
FCF/Assets	-23.37	-23.80
	(14.76)	(14.59)
CAPX/Sales	-2.321	-1.963
	(7.482)	(7.487)
Bank Characteristics		
Equator Bank		-9.933**
		(4.659)
Equator Bank * Sin		57.38***
		(14.17)
Constant	1,198***	1,194***
	(82.08)	(82.21)
Observations	5,446	5,446
Adjusted R-squared	0.436	0.437
Rating Dummies	Yes	Yes
Loan Characteristics	Yes	Yes
Purpose	Yes	Yes
Year Fixed Effects	Yes	Yes
Clustered SE	borrower	borrower

5% level. In addition to the base specification, we also extend regression 4 of Table 2.2 by including firm level characteristics. As regression 2 in Table 2.3 shows, and similar to the results found in the DealScan sample, Equator banks charge lower spreads om average. However, they charge sin firms a higher spread relative to the average firm. Our results are contrary to our expectations, as we find a significantly lower spread for sin firms, which persist across samples and specifications. For the remainder of this paper, we will use regressions 1 and 4 from Table 2.2 and regression 2 from Table 2.3 as our main specifications. These regressions allow us to show results for the largest sample and/or for the most comprehensive specification.

2.5 Potential Explanations

To explain the unexpected results reported above, we analyze a number of potential explanations. In addition to the standard firm-level control variables, we control for the accrual quality of firms, following Kim, Park, and Wier (2012). We also capture borrower-lender relationships, given the effects these are known to have on bank lending according to Bharath, Dahiya, Saunders, and Srinivasan (2011). Third, we control for the co-movement of a firm's equity with the market, as measured by firm beta. We want to determine whether sin firms are less cyclical than other firms and if this can explain the lower spreads observed. And lastly, following Aivazian, Qiu, and Rahaman (2015) we control for the organizational structure. Here we want to test whether firms with diversified operations receive beneficial loan terms.

2.5.1 Financial Reporting

We control for accrual quality following evidence that sin firms have more prudent reporting (Kim, Park, and Wier, 2012). Dechow and Dichev (2002) take the view that earnings that map more closely into cash are more desirable. This follows from the premise that one of the primary objectives of financial reporting is to provide information to investors and creditors to assess future cash flows. Better financial reporting leads to lower information risk. Accrual quality tells us about the mapping of accounting earnings into cash flows. Relatively poor accruals quality weakens this mapping, increasing information risk (Francis, LaFond, Olsson, and Schipper, 2005). The authors also show that accruals quality affects the cost of debt after controlling for other known factors, implying that the information risk is priced by investors. We use the modified version of the Dechow and Dichev (2002) model following Francis, LaFond, Olsson, and Schipper (2005). We obtain all accounting data from Compustat Annual. Accrual quality is specified as follows (all

variables are scaled by total assets):

$$TCA_{j,t} = \lambda_{0,j} + \lambda_{0,j}CFO_{j,t-1} + \lambda_{2,j}CFO_{j,t} + \lambda_{3,j}CFO_{j,t+1} + \lambda_{4,j}\Delta Rev_{j,t} + \lambda_{5,j}PPE_{j,t} + \nu_{j,t} \quad (2.3)$$

where,
$TCA_{j,t}$ = Firm j's total current accruals in year t ($\Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t}$), where,
$\Delta CA_{j,t}$ = firm j's change in current assets between year t-1 and t;
$\Delta CL_{j,t}$ = firm's j change in current liabilities between year t-1 and year t;
$\Delta Cash_{j,t}$ = firm j's change in cash between year t-1 and year t; and
$\Delta STDEBT_{j,t}$ = firm j's change in debt in current liabilities between year t-1 and t;
$DEPR_{j,t}$ = firm j's depreciation and amortization expense in year t.
$CFO_{j,t}$ = Firm j's cash flow from operations in year t, calculated as net income before extraordinary items in year t (NIBE) less total accruals (TA) in year t, where
$TA_{j,t} = \Delta CA_{j,t} - \Delta CL_{j,t} - \Delta Cash_{j,t} + \Delta STDEBT_{j,t} - DEPR_{j,t}$;
$DEPR_{j,t}$ = firm j's depreciation and amortization expense in year t.
$\Delta Rev_{j,t}$ = firm j's change in revenue between year $t-1$ and year t.
$PPE_{j,t}$ = firm j's gross value of PPE in year t.

For each firm-year we estimate Equation (2.3) using as many data points as possible, with a minimum of four years of data availability. These estimations yield firm- and year-specific residuals, $\nu_{j,t}$, which we then use to compute the accruals quality metric for each firm. We start by taking $\sigma(\nu_{j,t})$, the standard deviation of firm j's estimated residuals. A firm's earnings are deemed of high quality if the standard deviation is low, and of poor quality if the standard deviation is high. For our model, we compute accruals quality as $-\sigma(\nu_{j,t})$, the negative of accruals quality, to facilitate interpretation of the coefficient. In unreported results we also take the inverse of accruals quality, $\sigma(\nu_{j,t})^{-1}$ to test for robustness and the results remain unchanged. By taking the negative (inverse), a higher value of the coefficient is in line with better earnings quality. Some might argue that accruals are used in an opportunistic manner, to window-dress and mislead users of financial statements. Following Dechow and Dichev (2002) we do not attempt to disentangle "intentional" from unintentional errors, because both imply low-quality accruals. The authors argue that even in the absence of intentional earnings management, accruals quality will systematically be related to firm and industry characteristics. We control for accruals quality in Table 2.4 regressions 1 and 2. As results show, accruals quality does indeed have a negative relationship with spread, significant at the 1% level. Accruals quality cannot, however, explain the preferential treatment sin firms receive in the way of lower spreads.

In order to test the sensitivity of the results to the measure of accruals quality used, we compute different proxies for financial reporting quality. For our second measure we

consider the ability of earnings and its components to predict future cash flows. For the this model, dubbed Accruals Quality Method 2, we follow Kim, Park, and Wier (2012), Dechow, Kothari, and L Watts (1998) and Barth, Cram, and Nelson (2001). We compute the extent to which earnings and its components can predict future cash flows as follows (all variables are scaled by total assets):

$$CFO_{j,t+1} = \Phi_0 + \Phi_1 CFO_{j,t} + \Phi_2 \Delta AR_{j,t} + \Phi_3 \Delta INVENT_{j,t} + \Phi_4 \Delta AP_{j,t} + \Phi_5 DEPR_{j,t} + \Phi_6 \Delta OTHER_{j,t} + \kappa_{j,t+1} \quad (2.4)$$

where, $CFO_{j,t+1}$ and $CFO_{j,t}$ are the cash from operations in years $t+1$ and t for each firm j adjusted for the accrual portion of extraordinary items in the respective years; $\Delta AR_{j,t}$ is the change in accounts receivable for firm j; $\Delta AP_{j,t}$ is the change in accounts payable and accrued liabilities for firm j; $DEPR_{j,t}$ is the depreciation and amortization expense in year t for firm j; and $\Delta OTHER_{j,t}$ represents all other accruals, computed as $(NIBE - (CFO + \Delta AR + \Delta INVENT - \Delta AP - DEPR))$.

The residuals from Equation (2.4) capture the deviation of earnings and components in predicting future cash flows. Similar to our first measure of accruals quality, we take the standard deviation of the residuals, i.e., $\sigma(\kappa_{t+1})$. Again, we take the negative of this measure -$\sigma(\kappa_{t+1})$, which means that a higher residual volatility shows that earnings are better able to predict future cash flows, implying higher earnings quality. As results reported in Table 2.4 regressions 3 and 4 show, using this proxy for accruals quality does not change our results in a material manner.

Lastly, we follow Francis, LaFond, Olsson, and Schipper (2004) in controlling for earnings persistence and earnings predictability using Equation (2.5). Persistent earnings are desirable because it means they are recurring. We follow the authors and measure earnings persistence as the slope coefficient from the regressions of current earnings on lagged earnings, as specified in Equation (2.5).

$$NI_{i,t} = \alpha_i + \beta_i NI_{i,t-1} + \epsilon_{i,t} \quad (2.5)$$

Here, a β_i close to 1 implies highly persistent earnings, while small β_i imply transitory earnings. Earnings predictability is measured as above, i.e. $\sigma(\epsilon_{i,t})$, and as above, we take the negative of this measure to conform with the ordering attributes applied throughout. As results show, persistent earnings do indeed lead to a lower spread, however, they do not change the fact that sin firms have a lower spread relative to otherwise similar firms.

2.5.2 Are sin industries anti-cyclical?

Hong and Kacperczyk (2009) characterize sin stocks by calculating market betas for Fama and French (1997) industry groups. In their paper, the beer and smoke industries appear to have somewhat lower betas than other industries, whereas the gaming sector's beta

Table 2.4: Potential Explanations - Financial Reporting

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for the matched DealScan-Compustat sample. This sample includes a wide array of firm-level control variables. Our main variable of interest is the sin dummy variable (Sin). In order to maintain a parsimonious specification, while still controlling for industry effects, we include a comparable industry dummy (Comparable). The Comparable dummy variable takes unity for firms in comparable industries, i.e. industry group 2 (food) and 3 (soda) and 43 (meals, restaurants, hotels, and motels), and when firms are sin firms. This allows for an immediate test of differences between sin firms and firms in comparable industries. Any comparable firm will have β_2 mean spread in bp. A sin firm on the other hand will have $\beta_1 + \beta_2$ on average. This means that the difference between sin, and all comparable firms equals $(\beta_1 + \beta_2) - \beta_2 = \beta_1$. We control for different firm level characteristics known to affect loan spreads. In addition to the standard firm-level characteristics, we control for the accrual quality of firms, following Kim, Park, and Wier (2012). We also control for loan characteristics following existing literature. Lastly, we control for whether banks are equator banks. Banks make an explicit social association by joining the equator principles, allowing for the assumption that these banks shun socially irresponsible products and/or the producing firm. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sin	-36.65*	-52.59**	-49.85**	-65.90**	-39.65*	-57.44**	-40.24*	-59.14**
	(20.34)	(22.65)	(24.34)	(27.45)	(21.51)	(23.77)	(21.18)	(23.27)
Comparable	29.38	30.37	42.23*	43.09*	27.45	28.56	27.88	29.43
	(20.53)	(20.79)	(24.28)	(24.61)	(21.33)	(21.59)	(20.69)	(20.98)
Size	13.63**	13.93**	6.768	6.979	9.671*	9.954*	11.39**	11.77**
	(5.399)	(5.439)	(5.517)	(5.563)	(5.271)	(5.301)	(5.233)	(5.261)
Tangibility	24.86***	24.43***	17.83**	17.88**	12.69*	12.24*	12.50*	11.78*
	(7.095)	(7.036)	(7.813)	(7.836)	(6.879)	(6.855)	(6.823)	(6.793)
Leverage	99.62***	99.92***	92.95***	93.08***	96.80***	97.16***	93.78***	94.05***
	(16.90)	(16.94)	(17.57)	(17.61)	(16.90)	(16.94)	(16.87)	(16.90)
Z - Score	-6.684*	-6.678*	-8.598*	-8.566*	-8.889**	-8.860**	-8.515**	-8.482**
	(3.936)	(3.939)	(4.697)	(4.693)	(4.212)	(4.211)	(4.193)	(4.191)
Profitability	-209.9***	-208.1***	-217.7***	-217.6***	-192.2***	-190.8***	-169.2***	-166.6***
	(42.70)	(42.83)	(48.08)	(48.21)	(42.69)	(42.81)	(42.49)	(42.62)
FCF/Assets	-19.04	-19.18	-15.75	-16.00	-24.91*	-25.21*	-27.45*	-27.72*
	(14.03)	(13.90)	(16.37)	(16.17)	(14.62)	(14.47)	(14.68)	(14.54)
CAPX/Sales	-6.107	-5.674	-3.038	-2.827	-2.286	-1.887	-3.014	-2.461
	(8.209)	(8.252)	(8.117)	(8.142)	(7.504)	(7.514)	(7.672)	(7.635)
Accrual Quality	-733.3***	-727.1***						
	(178.0)	(177.5)						
Accrual Quality (Method 2)			-0.0422**	-0.0420**				
			(0.0206)	(0.0203)				
Earnings Predictability					-2.396	-2.380		
					(1.540)	(1.535)		
Earnings Persistence							-36.70***	-37.00***
							(9.759)	(9.796)
Constant	1,172***	1,169***	1,189***	1,188***	1,112***	1,114***	1,127***	1,127***
	(75.01)	(75.21)	(89.05)	(89.29)	(84.79)	(83.59)	(84.28)	(82.64)
Observations	5,184	5,184	4,432	4,432	5,352	5,352	5,216	5,216
Adjusted R-squared	0.443	0.444	0.440	0.441	0.433	0.433	0.431	0.433
Rating Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower	borrower	borrower	borrower	borrower

is comparatively high. This difference in betas might also have an effect on how stable banks deem certain firms/ industries to be. We compute the firm-level beta following this premise. We obtain monthly return data from CRSP and use CRSP-Compustat merged to match these to our sample of Compustat firms. We use the value weighted CRSP market index as the market factor. The betas are computed over a 60-month time

period, with a minimum of 24 months of data availability for each firm. We then add the firm-level beta to our regressions as a control variable. The idea here is that if sin firms have lower betas than other firms, then banks might consider them hedge opportunities, and as such, provide them with preferential loan terms.

We control for the borrower beta in specification 9 and 10 in Table 2.5. As expected, beta has a positive relationship with spread, implying that more cyclical firms pay higher spreads than less cyclical firms. However, as the sin coefficient shows, the cyclicality of firms cannot explain the fact that sin firms have lower spreads than otherwise similar firms.

2.5.3 Relationship Lending

Following Bharath, Dahiya, Saunders, and Srinivasan (2011), we employ two proxies for the bank-borrower relationship. First, we construct a relationship dummy variable, which takes a value 1 if borrower i borrowed from lead arranger b in the past five years. If a borrower has a deal with multiple tranches, we do not consider those in our relationship dummy variable as these will likely bias the relationship effect upward.

Second, we construct a variable, relationship number, which measures the number of loans by lead arranger b to borrower i to all loans of borrower i in the past five years, calculated as follows:

$$\text{Relationship Number} = \frac{\text{Number of loans by lender } b \text{ to borrower } i \text{ in the past five years}}{\text{Total number of loans by borrower } i \text{ in the past five years}} \tag{2.6}$$

This measure returns a continues variable, which allows for an estimate of the strength of the relationship between borrower i and lender b. In cases where there are multiple lead arrangers we take the highest relationship value. Regressions 3 and 4 in Table 2.5 show, the coefficient for the relationship proxies is negative, implying that repetitive borrowing from the same banks leads to lower spreads. However, borrower-lender relationship does not explain the preferential treatment sin firms receive from banks. Regressions 5 and 6 are in line with the simple relationship dummy, that is, a bank-borrower relationship leads to significantly lower spreads, however, the sin effect persists.

Table 2.5: Potential Explanations - Relationship and Beta

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for the matched DealScan-Compustat sample with additional potential explanatory variables. This sample includes a wide array of firm-level control variables. Our variable of interest is the sin dummy variable. The comparable dummy variable takes unity for firms in comparable industries, industry group 2 (food) and 3 (soda) and 43 (meals, restaurants, hotels, and motels), and when firms are sin firms. This allows for an immediate test of differences between sin firms and firms in comparable industries. In addition to the standard firm-level characteristics, we control for the co-movement of a firm's equity with the market measured by firm beta, to identify whether the cyclicality of firms has an effect on their cost of debt. We also control for borrower-lender relationships, given the effects these are known to have on bank lending Bharath, Dahiya, Saunders, and Srinivasan (2011) in regressions 3 through 6. We also control for loan characteristics following existing literature. Lastly, we control for whether banks are equator banks. Banks make an explicit social association by joining the equator principles, allowing for the assumption that these banks shun socially irresponsible products and/or the producing firm. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Borrower Characteristics						
Sin	-53.93**	-73.85**	-39.82*	-56.95**	-40.00*	-57.21**
	(26.47)	(29.09)	(21.09)	(23.14)	(21.08)	(23.09)
Comparable	46.22*	47.05*	26.49	27.47	26.68	27.66
	(27.11)	(27.40)	(21.12)	(21.37)	(21.13)	(21.38)
Size	12.49**	12.85**	10.47**	10.70**	10.62**	10.84**
	(6.324)	(6.366)	(5.179)	(5.205)	(5.097)	(5.120)
Tangibility	12.68	12.08	13.77**	13.40**	13.54**	13.17*
	(8.487)	(8.448)	(6.795)	(6.761)	(6.773)	(6.740)
Leverage	109.9***	110.7***	99.41***	99.76***	99.71***	100.1***
	(25.85)	(25.89)	(16.39)	(16.43)	(16.37)	(16.41)
Z - Score	-9.861**	-9.721**	-9.022**	-9.005**	-9.082**	-9.063**
	(4.895)	(4.921)	(4.108)	(4.105)	(4.106)	(4.102)
Profitability	-194.1***	-193.5***	-194.2***	-192.7***	-194.3***	-192.7***
	(52.50)	(52.76)	(42.56)	(42.66)	(42.55)	(42.65)
FCF/Assets	-19.33	-18.59	-23.52	-23.95	-23.44	-23.86
	(20.25)	(20.20)	(14.71)	(14.55)	(14.74)	(14.57)
CAPX/Sales	4.793	6.139	-2.369	-2.022	-2.366	-2.014
	(12.27)	(12.32)	(7.432)	(7.446)	(7.464)	(7.474)
Beta	2.491	2.503				
	(1.551)	(1.553)				
Bank Characteristics						
Equator Bank		-11.33**		-10.30**		-10.45**
		(4.890)		(4.245)		(4.254)
Equator Bank * Sin		45.57***		47.41***		48.19***
		(12.38)		(11.41)		(11.37)
Relationship (Number)			-19.20	-18.60		
			(12.13)	(12.20)		
Relationship (Dummy)					-6.038	-5.857
					(5.587)	(5.622)
Constant	907.7***	915.7***	1,195***	1,192***	1,195***	1,192***
	(71.83)	(70.62)	(82.31)	(82.42)	(82.46)	(82.56)
Observations	3,822	3,822	5,446	5,446	5,446	5,446
Adjusted R-squared	0.435	0.436	0.437	0.438	0.437	0.437
Rating Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Purpose	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower	borrower	borrower

2.5.4 Corporate Diversification

Corporate diversification is widely thought to positively affect a firms cost of capital. Aivazian, Qiu, and Rahaman (2015) study the effect of a corporation's organizational structure on its financing capacity. They use the diversification strategy of the firm as an identification tool for organizational structure and analyze the effect of structure on a firm's financing capacity. Their results show that diversified firms have significantly lower loan rates than comparable focused firms, without being subject to restrictive non-price terms. These results indicate that coinsurance effects in investment opportunities and cash flows reduce the spreads firms pay on their loans.

Following these results, we use two different measures of corporate diversification to test whether this has an effect on the lower spreads to sin firms we observe. Our first measure is a dummy variable that takes a value 1 when a firm operates in more than one unique four-digit SIC code industry. We also construct a similar measure based on two-digit SIC codes, which implies greater diversification by firms as they operate in entirely different industries. The second measure is an integer, enumerating the number of unique SIC code industries a firm operates in. The results for diversification can be seen in Table 2.6 for the Dealscan and the Compustat samples. The results for the full sample, in regressions 1 and 2, show that corporate diversification is associated with significantly lower spreads. However, including diversification as an additional variable does not affect the coefficient of the sin dummy. For the Compustat sample in regressions 3 and 4 the coefficient on diversification is not significant. Most important to note in our context is that including diversification does not affect the sin coefficient in the Compustat sample either. Our results remain largely the same for all measures of corporate diversification. Therefore, for brevity, we only report the results for the second measure.

Lastly, we include all four potential explanations in one specification to rule out that it is a joint effect of these different factors which leads to lower spreads for sin firms. Tables 2.7 and 2.8 show the results for these specifications, and as can be seen, the results remain qualitatively similar across different specifications, and the sin effect persists.

2.6 Robustness

In our first robustness test, we control for industry fixed effects for both the full DealScan sample and the Compustat sample. As Table 2.9 shows, including industry fixed effects, instead of the comparable industry dummy, does not materially affect the results relative to our main regressions in Tables 2.2 and 2.3. The results remain qualitatively and quantitatively similar. Table 2.10 shows results for the Compustat sample including industry fixed effects. We see a little more variability in results for this sample, which is expected given the smaller sample size. For regression 1, the economic magnitude of sin decreases and the significance disappears. However, regression 2 is largely in line with previous results. Thus, we conclude that even after controlling for all industries, the sin

Table 2.6: Potential Explanations - Diversification

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for the full DealScan sample in regressions 1 and 2 and for the matched Dealscan-Compustat sample in regressions 3 and 4. In the Dealscan sample, firm characteristics are limited to credit ratings and borrower sales, while in the matched Dealscan-Compustat sample we can control for a wide array of firm-level characteristics. Our main variable of interest is the sin dummy variable (Sin). In order to maintain a parsimonious specification, while still controlling for industry effects, we include a comparable industry dummy (Comparable). The Comparable dummy variable takes unity for firms in comparable industries, i.e. industry group 2 (food) and 3 (soda) and 43 (meals, restaurants, hotels, and motels), and when firms are sin firms. This allows for an immediate test of differences between sin firms and firms in comparable industries. Any comparable firm will have β_2 mean spread in bp. A sin firm on the other hand will have $\beta_1 + \beta_2$ on average. This means that the difference between sin, and all comparable firms equals $(\beta_1 + \beta_2) - \beta_2 = \beta_1$. We control for loan characteristics following existing literature. Lastly, we control for whether banks are equator banks. Banks make an explicit social association by joining the equator principles, allowing for the assumption that these banks shun socially irresponsible products and/or the producing firm. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Sin	-32.62***	-37.72***	-40.37*	-57.59**
	(10.12)	(12.00)	(21.22)	(23.32)
Comparable	17.71***	18.93***	26.89	27.87
	(5.163)	(5.181)	(20.94)	(21.18)
Size (Dealscan)	-4.220***	-3.865***		
	(1.215)	(1.215)		
Size			10.14*	10.36**
			(5.198)	(5.222)
Tangibility			12.54*	12.19*
			(6.920)	(6.886)
Leverage			99.52***	99.87***
			(16.37)	(16.41)
Z - Score			-9.803**	-9.782**
			(4.248)	(4.245)
Profitability			-190.8***	-189.2***
			(42.89)	(42.99)
FCF/Assets			-23.58	-24.02
			(14.88)	(14.70)
CAPX/Sales			-2.413	-2.034
			(7.514)	(7.513)
Diversification	-4.853***	-4.895***	1.295	1.394
	(1.520)	(1.521)	(3.442)	(3.451)
Constant	1,327***	1,304***	1,197***	1,194***
	(35.94)	(36.04)	(82.01)	(82.12)
Observations	36,994	36,994	5,442	5,442
Adjusted R-squared	0.294	0.297	0.437	0.437
Rating Dummies	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
Bank Characteristics	No	Yes	No	Yes
Purpose	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

Table 2.7: Potential Explanations - Full Specification

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for the matched DealScan-Compustat sample. This sample includes a wide array of firm-level control variables. Our main variable of interest is the sin dummy variable (Sin). In order to maintain a parsimonious specification, while still controlling for industry effects, we include a comparable industry dummy (Comparable). The Comparable dummy variable takes unity for firms in comparable industries, i.e. industry group 2 (food) and 3 (soda) and 43 (meals, restaurants, hotels, and motels), and when firms are sin firms. This allows for an immediate test of differences between sin firms and firms in comparable industries. Any comparable firm will have β_2 mean spread in bp. A sin firm on the other hand will have $\beta_1 + \beta_2$ on average. This means that the difference between sin, and all comparable firms equals $(\beta_1 + \beta_2) - \beta_2 = \beta_1$. We control for different firm level characteristics known to affect loan spreads. In addition to the standard firm-level characteristics, we control for the accrual quality of firms, following Kim, Park, and Wier (2012), we also control for the co-movement of a firm's equity with the market measured by firm beta, to identify whether the cyclicality of firms has an effect on their cost of debt. And we control for borrower-lender relationships, given the effects these are known to have on bank lending Bharath, Dahiya, Saunders, and Srinivasan (2011). This table shows all potential explanations. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Borrower Characteristics								
Sin	-50.53*	-69.40**	-71.91**	-91.99***	-55.26**	-75.36**	-56.46**	-77.97***
	(25.84)	(28.69)	(30.07)	(33.41)	(26.71)	(29.28)	(26.19)	(28.57)
Comparable	47.63*	48.52*	64.46**	64.99**	46.52*	47.34*	46.28*	47.42*
	(26.91)	(27.22)	(31.02)	(31.35)	(27.44)	(27.72)	(26.32)	(26.60)
Size	15.96**	16.30***	8.016	8.297	12.45**	12.78**	13.26**	13.71**
	(6.256)	(6.300)	(6.001)	(6.056)	(6.163)	(6.206)	(6.082)	(6.130)
Tangibility	21.67**	21.04**	12.49	12.53	11.86	11.29	12.48	11.73
	(8.836)	(8.777)	(8.678)	(8.706)	(8.476)	(8.440)	(8.576)	(8.527)
Leverage	112.5***	113.2***	107.5***	108.2***	109.8***	110.6***	103.6***	104.1***
	(26.04)	(26.09)	(27.79)	(27.85)	(25.69)	(25.72)	(25.88)	(25.89)
Z - Score	-7.619*	-7.513	-9.770*	-9.669*	-10.42**	-10.28**	-9.865**	-9.684*
	(4.608)	(4.636)	(5.043)	(5.062)	(5.023)	(5.051)	(5.006)	(5.042)
Profitability	-213.4***	-212.6***	-213.9***	-214.4***	-188.9***	-188.3***	-157.3***	-155.4***
	(51.04)	(51.29)	(56.24)	(56.56)	(53.05)	(53.28)	(51.40)	(51.60)
CAPX/Sales	5.493	6.878	12.38	13.32	5.225	6.624	0.835	2.451
	(11.95)	(12.00)	(12.74)	(12.75)	(12.33)	(12.39)	(12.35)	(12.39)
FCF/Assets	-13.31	-12.53	-21.98	-21.66	-20.45	-19.74	-23.47	-22.38
	(17.54)	(17.52)	(19.84)	(19.72)	(20.31)	(20.24)	(19.99)	(19.99)
Beta	2.274*	2.286*	2.202	2.253	2.480	2.489	2.268	2.274
	(1.234)	(1.244)	(1.716)	(1.737)	(1.516)	(1.517)	(1.449)	(1.449)
Earnings Quality	-827.8***	-821.7***						
	(218.2)	(217.8)						
Earnings Quality (Method 2)			-0.0459	-0.0467				
			(0.0297)	(0.0296)				
Earnings Predictability					-0.183	-0.206		
					(2.251)	(2.254)		
Earnings Persistence							-44.88***	-46.03***
							(12.60)	(12.76)
Diversification	2.003	2.192	2.390	2.601	2.511	2.743	2.091	2.306
	(3.975)	(3.981)	(4.281)	(4.290)	(3.962)	(3.970)	(4.087)	(4.094)
Bank Characteristics								
Equator Bank		-12.21**		-9.468*		-11.82**		-14.17**
		(5.401)		(5.645)		(5.319)		(5.501)
Equator Bank × Sin		53.38***		56.09***		57.48***		60.63***
		(14.81)		(15.36)		(14.53)		(14.19)
Relationship (Dummy)	-6.573	-6.386	-5.929	-5.886	-6.828	-6.677	-7.486	-7.283
	(6.713)	(6.754)	(7.204)	(7.236)	(6.691)	(6.724)	(6.588)	(6.627)
Constant	881.8***	888.8***	1,057***	1,056***	1,052***	1,050***	1,058***	1,056***
	(71.20)	(70.23)	(104.0)	(103.3)	(93.55)	(93.13)	(93.52)	(93.12)
Observations	3,783	3,783	3,305	3,305	3,818	3,818	3,716	3,716
Adjusted R-squared	0.443	0.445	0.444	0.445	0.435	0.437	0.435	0.437
Rating Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower	borrower	borrower	borrower	borrower

Table 2.8: Potential Explanations - Full Specification Continued

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for the matched DealScan-Compustat sample. This sample includes a wide array of firm-level control variables. Our main variable of interest is the sin dummy variable (Sin). In order to maintain a parsimonious specification, while still controlling for industry effects, we include a comparable industry dummy (Comparable). The Comparable dummy variable takes unity for firms in comparable industries, i.e. industry group 2 (food) and 3 (soda) and 43 (meals, restaurants, hotels, and motels), and when firms are sin firms. This allows for an immediate test of differences between sin firms and firms in comparable industries. Any comparable firm will have β_2 mean spread in bp. A sin firm on the other hand will have $\beta_1 + \beta_2$ on average. This means that the difference between sin, and all comparable firms equals $(\beta_1 + \beta_2) - \beta_2 = \beta_1$. We control for different firm level characteristics known to affect loan spreads. In addition to the standard firm-level characteristics, we control for the accrual quality of firms, following Kim, Park, and Wier (2012), we also control for the co-movement of a firm's equity with the market measured by firm beta, to identify whether the cyclicality of firms has an effect on their cost of debt. And we control for borrower-lender relationships, given the effects these are known to have on bank lending Bharath, Dahiya, Saunders, and Srinivasan (2011). This table shows all potential explanations. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Borrower Characteristics								
Sin	-50.21*	-68.98**	-71.54**	-91.48***	-54.91**	-74.89**	-56.13**	-77.53***
	(25.93)	(28.86)	(30.22)	(33.66)	(26.80)	(29.45)	(26.22)	(28.69)
Comparable	47.29*	48.19*	64.12**	64.65**	46.16*	46.99*	45.94*	47.08*
	(26.95)	(27.25)	(31.09)	(31.42)	(27.48)	(27.76)	(26.29)	(26.58)
Size	15.77**	16.12**	7.876	8.153	12.26*	12.59**	13.06**	13.51**
	(6.372)	(6.419)	(6.124)	(6.182)	(6.280)	(6.325)	(6.188)	(6.238)
Tangibility	21.75**	21.12**	12.58	12.61	11.98	11.41	12.65	11.89
	(8.824)	(8.766)	(8.658)	(8.687)	(8.466)	(8.430)	(8.558)	(8.510)
Leverage	112.1***	112.8***	107.1***	107.8***	109.4***	110.2***	103.2***	103.7***
	(26.06)	(26.12)	(27.84)	(27.90)	(25.71)	(25.75)	(25.87)	(25.88)
Z - Score	-7.533	-7.432	-9.700*	-9.604*	-10.32**	-10.18**	-9.735*	-9.558*
	(4.606)	(4.634)	(5.038)	(5.056)	(5.021)	(5.049)	(5.005)	(5.041)
Profitability	-213.1***	-212.3***	-213.7***	-214.3***	-188.6***	-188.0***	-156.9***	-155.0***
	(51.04)	(51.29)	(56.23)	(56.54)	(53.03)	(53.26)	(51.41)	(51.60)
CAPX/Sales	5.783	7.147	12.61	13.53	5.529	6.908	1.178	2.778
	(11.84)	(11.89)	(12.60)	(12.62)	(12.22)	(12.28)	(12.23)	(12.27)
FCF/Assets	-13.38	-12.61	-21.93	-21.62	-20.51	-19.81	-23.60	-22.52
	(17.48)	(17.46)	(19.82)	(19.71)	(20.24)	(20.18)	(19.92)	(19.92)
Beta	2.291*	2.302*	2.218	2.267	2.497*	2.505*	2.290	2.295
	(1.237)	(1.246)	(1.716)	(1.737)	(1.514)	(1.515)	(1.448)	(1.448)
Earnings Quality	-825.6***	-819.6***						
	(218.4)	(218.1)						
Earnings Quality (Method 2)			-0.0454	-0.0463				
			(0.0297)	(0.0295)				
Earnings Predictability					-0.201	-0.223		
					(2.238)	(2.242)		
Earnings Persistence							-44.75***	-45.89***
							(12.62)	(12.78)
Diversification	2.152	2.334	2.460	2.662	2.664	2.888	2.228	2.438
	(3.974)	(3.980)	(4.288)	(4.298)	(3.959)	(3.968)	(4.087)	(4.095)
Bank Characteristics								
Equator Bank		-12.12**		-9.377*		-11.73**		-14.10**
		(5.394)		(5.660)		(5.312)		(5.484)
Equator Bank × Sin		53.05***		55.72***		57.15***		60.27***
		(14.76)		(15.37)		(14.46)		(14.10)
Relationship (Number)	-20.70	-20.04	-17.48	-17.03	-21.63	-21.05	-24.23*	-23.60
	(14.59)	(14.69)	(16.04)	(16.14)	(14.50)	(14.58)	(14.31)	(14.38)
Constant	880.7***	887.8***	1,057***	1,057***	1,051***	1,050***	1,058***	1,056***
	(70.74)	(69.80)	(103.8)	(103.1)	(93.34)	(92.93)	(93.34)	(92.96)
Observations	3,783	3,783	3,305	3,305	3,818	3,818	3,716	3,716
Adjusted R-squared	0.444	0.445	0.444	0.445	0.436	0.437	0.435	0.437
Rating Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower	borrower	borrower	borrower	borrower

Table 2.9: Full DealScan Sample - Industry Fixed Effects

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for the full DealScan sample. In this sample, firm characteristics are limited to credit ratings and borrower sales. Our main variable of interest is the sin dummy variable (Sin). We control for industry by including industry fixed effects, instead of our choice of Comparable. This table is a replica of Table 2.2 - Full DealScan Sample with industry fixed effects. We control for loan characteristics following existing literature. Lastly, we control for whether banks are equator banks. Banks make an explicit social association by joining the equator principles, allowing for the assumption that these banks shun socially irresponsible products and/or the producing firm. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Sin	-33.54***	-17.18*	-24.30**	-28.54**
	(9.293)	(9.575)	(9.729)	(11.80)
Size			-4.362***	-3.847***
			(1.234)	(1.237)
Bank Characteristics				
Equator Bank				-28.03***
				(2.391)
Equator Bank × Sin				16.78
				(19.33)
Constant	306.2***	1,318***	1,323***	1,299***
	(5.841)	(37.67)	(35.93)	(36.01)
Observations	86,513	45,423	37,310	37,310
Adjusted R-squared	0.128	0.289	0.296	0.299
Rating Dummies	Yes	Yes	Yes	Yes
Purpose	Yes	Yes	Yes	Yes
Loan Characteristics	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

effect remains economically and statistically significant in most cases. This shows that our results are not driven by our choice of industry control.

We also want to make sure that our results are not being driven by a specific period in our sample. Tables 2.11 and 2.12 show the results for a sub-period starting in 1993 and ending in 2012. We choose this time period, because coverage of the syndicated loans significantly increases starting in 1993 relative to previous years. As results show, the sin effect is not being driven by a phenomenon early in the sample nor by any potential biases due to reduced database coverage, as the results remain robust to those shown in previous results.

Table 2.10: Compustat Sample - Industry Fixed Effects

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for the matched DealScan-Compustat sample. This sample includes a wide array of firm-level control variables. Our main variable of interest is the sin dummy variable (Sin). We control for industry by including industry fixed effects, instead of our choice of Comparable. This table is a replica of Table 2.2 - Full DealScan Sample with industry fixed effects. We control for different firm level characteristics known to affect loan spreads. We also control for loan characteristics following existing literature. Lastly, we control for whether banks are equator banks. Banks make an explicit social association by joining the equator principles, allowing for the assumption that these banks shun socially irresponsible products and/or the producing firm. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
Borrower Characteristics		
Sin	-13.70	-30.72***
	(9.486)	(11.10)
Size	10.39**	10.70**
	(4.830)	(4.873)
Tangibility	7.724	7.746
	(8.455)	(8.458)
Leverage	99.31***	99.65***
	(16.35)	(16.40)
Z - Score	-12.13***	-12.05***
	(4.272)	(4.279)
Profitability	-197.4***	-197.1***
	(45.15)	(45.34)
FCF/Assets	-25.62*	-26.04*
	(15.45)	(15.25)
CAPX/Sales	-4.777	-4.475
	(7.127)	(7.081)
Bank Characteristics		
Equator Bank		-8.260*
		(4.712)
Equator Bank × Sin		53.01***
		(14.44)
Constant	1,230***	1,228***
	(82.81)	(82.91)
Observations	5,446	5,446
Adjusted R-squared	0.442	0.443
Rating Dummies	Yes	Yes
Loan Characteristics	Yes	Yes
Purpose	Yes	Yes
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Clustered SE	borrower	borrower

Table 2.11: Full DealScan Sub-Sample

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for a sub-period (1993-2012) of the DealScan sample. In this sample, firm characteristics are limited to credit ratings and borrower sales. Our main variable of interest is the sin dummy variable (Sin). In order to maintain a parsimonious specification, while still controlling for industry effects, we include a comparable industry dummy (Comparable). The Comparable dummy variable takes unity for firms in comparable industries, i.e. industry group 2 (food) and 3 (soda) and 43 (meals, restaurants, hotels, and motels), and when firms are sin firms. This allows for an immediate test of differences between sin firms and firms in comparable industries. Any comparable firm will have β_2 mean spread in bp. A sin firm on the other hand will have $\beta_1 + \beta_2$ on average. This means that the difference between sin, and all comparable firms equals $(\beta_1 + \beta_2) - \beta_2 = \beta_1$. We control for loan characteristics following existing literature. Lastly, we control for whether banks are equator banks. Banks make an explicit social association by joining the equator principles, allowing for the assumption that these banks shun socially irresponsible products and/or the producing firm. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Borrower Characteristics				
Sin	-16.12*	-13.37	-23.33**	-29.17**
	(9.501)	(9.285)	(9.402)	(11.44)
Comparable	4.428	12.95***	15.39***	16.44***
	(4.370)	(4.904)	(5.258)	(5.267)
Size			-5.753***	-5.436***
			(1.274)	(1.274)
Bank Characteristics				
Equator Bank				-23.79***
				(2.423)
Equator Bank × Sin				18.41
				(19.59)
Constant	321.6***	1,508***	1,427***	1,410***
	(8.251)	(40.95)	(41.59)	(41.63)
Observations	76,348	39,973	33,032	33,032
Adjusted R-squared	0.134	0.309	0.317	0.319
Rating Dummies	Yes	Yes	Yes	Yes
Loan Characteristics	No	Yes	Yes	Yes
Purpose	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

Table 2.12: Compustat Sub-Sample

We estimate the cross-sectional relation between loan spreads and firm characteristics, loan characteristics, and bank characteristics for a sub-period (1993-2012) of the matched DealScan-Compustat sample. This sample includes a wide array of firm-level control variables. Our main variable of interest is the sin dummy variable (Sin). In order to maintain a parsimonious specification, while still controlling for industry effects, we include a comparable industry dummy (Comparable). The Comparable dummy variable takes unity for firms in comparable industries, i.e. industry group 2 (food) and 3 (soda) and 43 (meals, restaurants, hotels, and motels), and when firms are sin firms. This allows for an immediate test of differences between sin firms and firms in comparable industries. Any comparable firm will have β_2 mean spread in bp. A sin firm on the other hand will have $\beta_1 + \beta_2$ on average. This means that the difference between sin, and all comparable firms equals $(\beta_1 + \beta_2) - \beta_2 = \beta_1$. We control for different firm level characteristics known to affect loan spreads. We also control for loan characteristics following existing literature. Lastly, we control for whether banks are equator banks. Banks make an explicit social association by joining the equator principles, allowing for the assumption that these banks shun socially irresponsible products and/or the producing firm. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
Borrower Charateristics		
Sin	-36.21*	-52.84**
	(19.95)	(21.79)
Comparable	25.61	26.36
	(19.50)	(19.62)
Size	10.59**	10.78**
	(5.176)	(5.189)
Tangibility	14.60**	14.26**
	(6.931)	(6.910)
Leverage	104.9***	105.4***
	(17.21)	(17.25)
Z - Score	-9.450**	-9.428**
	(3.899)	(3.897)
Profitability	-197.4***	-196.4***
	(44.68)	(44.87)
FCF/Assets	-25.19*	-25.70*
	(14.99)	(14.81)
CAPX/Sales	-3.238	-2.876
	(7.623)	(7.627)
Bank Characteristics		
Equator Bank		-9.333**
		(4.520)
Equator Bank × Sin		55.65***
		(14.30)
Constant	1,211***	1,209***
	(76.96)	(77.02)
Observations	5,221	5,221
Adjusted R-squared	0.450	0.450
Rating Dummies	Yes	Yes
Loan Characteristics	Yes	Yes
Purpose	Yes	Yes
Year Fixed Effects	Yes	Yes
Clustered SE	borrower	borrower

2.7 Conclusion

Our investigation focuses on the effects of social norms in the bank debt market by looking at the three industries identified by Hong and Kacperczyk (2009) as sin firms, namely alcohol, tobacco, and gaming. We compare the spreads on the loans of sin firms to the spreads on the loans of other, comparable, firms. If banks are norm-constrained institutions, then we would expect them to charge sin firms a higher spread on their loans. Alternatively, if banks are not norm-constrained, or neutral, then we would expect sin firms to have spreads similar to otherwise similar firms. Contrary to our expectations, we find that spreads on loans to borrowers in sin industries are consistently and significantly lower than spreads on loans to otherwise comparable firms. That is, we find that banks give sin firms preferential treatment, even after controlling for general firm, loan, and bank factors known to affect cost of debt.

In an attempt to explain these results, we control for various aspects which have been shown to affect sin firms and/or loan conditions. We start by controlling for earnings quality, following Kim, Park, and Wier (2012). Our results show that although better earnings quality does indeed have a negative relationship with loan spread, it does not explain away the lower spreads sin firms pay. We continue by controlling for bank-borrower relationships. Again, when there is such a relationship, spreads are on average lower, however, the sin effect persists. Third, we control for firm beta. Here we follow the premise that when firms are anti-cyclical, they might be seen as a hedge opportunity by banks. We find that beta is positively related to loan spreads, but controlling for this does not eliminate the negative sin effect on spreads. Lastly, we control for organizational structure, following the theory that corporate diversification is negatively related to a firm's cost of capital. Our evidence is inconclusive regarding the effect of diversification on spreads. In the Full DealScan sample, we find that corporate diversification is negatively related to spreads in a significant manner. These results are not supported by the Compustat sample however, where we find no significant relation between diversification and spreads. More importantly, controlling for diversification does not affect our sin coefficient. Our results remain qualitatively and quantitatively in line with our previous findings, which provide evidence of preferential treatment by banks to sin firms in the form of lower spreads. One potential explanation for our results, although not formally tested in this paper, is that banks know the true underlying value of their borrowers. Banks are potentially smarter than investors in their estimation of risk and are potentially better informed than market participants. One of the main reasons for this higher level of information hypothesis is that banks perform due diligence prior to lending to borrowers and therefore make more informed decisions and are less likely to overestimate risk. In conclusion, we show that sin firms enjoy lower spreads on their loans relative to otherwise similar firms. Our results remain qualitatively similar across different samples and different specifications.

Chapter 3

Split Ratings in the Syndicated Loan Market*

3.1 Introduction

Loan interest rates are set in accordance with the perceived riskiness of borrowers. Information on this riskiness is limited and difficult to obtain. Due to this information scarcity, banks face uncertainty in their assessment. As a result "good" borrowers may be overcharged and the underestimation of the risk of "bad" borrowers may result in too low rates.

In practice, the existence of Credit Rating Agencies (CRAs) seems to reduce this information uncertainty greatly. CRAs are specialized information gatherers that evaluate the riskiness inherent to a country, corporation or specific debt instrument (Bavaria, 2002). According to Frost (2007), large CRAs play two key important roles in capital markets. First, they play a valuation role through information dissemination to market participants. In this role, CRAs gather and analyze information relevant for assessing credit quality, and provide markets with the results of their analyses. The second role of CRAs is that of facilitating contracting, because letter ratings are seen as efficient credit quality benchmarks. These ratings are used widely, and rating-based constraints appear in loan agreements, bond covenants and other financial agreements, making their effects widespread and significant. The increasing worldwide presence of these agencies suggests that their services represent a valuable information source to creditors and investors (Sufi, 2009).

These credit ratings are useful for both the parties seeking and providing capital. For the former, credit ratings improve marketability (Becker and Milbourn, 2011), and non-speculative grade ratings open the door for investments from large financial institutions (Boot, Milbourn, and Schmeits, 2005). The providers of capital use ratings as an indicator of risk and likely repayment of securities. They supplement, or are a fundamental input,

*This chapter is co-authored with Stefanie Kleimeier (Maastricht University, University of Stellenbosch Business School and Open University).

in their own credit risk assessments. According to Bongaerts, De Jong, and Driessen (2011), credit ratings reflect the creditworthiness of an issue or issuer. Rating agencies do however, have some discretion in the philosophy underlying their rating system and are not required to make their rating methodology public. More importantly, Jorion, Liu, and Shi (2005) posit that credit analysts at rating agencies have access to confidential information that is not available to other securities professionals. This, in turn, has two effects, one is that the ratings of these agencies are impossible to measure using solely public information, and second, this potentially increases the value of ratings to the public. While the repeated interactions between banks and firms does provide banks with some non-public information, it is likely that the CRAs still have more information than the banks themselves, such that their ratings may more accurately reflect the inherent risks.

Ratings are also widely used in determining loan conditions. For example, Sufi (2007) and Asquith, Beatty, and Weber (2005) state that loans often have pricing that is mainly dependent on the borrower's credit rating. Sufi (2007) also posits that anecdotal evidence from practitioner interviews suggests that the existence of a third-party credit rating makes obtaining loan approvals easier. Bosch and Steffen (2011) find that credit rating certification is critical to the supply of debt financing. Faulkender and Petersen (2005) show that issuer credit ratings are associated with higher leverage ratios. Sufi (2009) finds that loan ratings allow borrowers to expand their set of creditors, in line with the argument that credit ratings are critical in the attraction of investors without specialized monitoring or screening skills.

An indication of the importance of credit ratings in our sample is that credit ratings alone explain 53% of variation in loan spreads. Confirming that credit ratings play a significant role in determining loan pricing. The availability of credit ratings is particularly important in syndicated loans, as it allows lead arrangers to easily communicate information about the borrower's credit risk to potential participant banks in the syndicate. As such, having a credit rating decreases the uncertainty about the firm's credit risk, such that rates may be set more accurately.

The information role of credit ratings is, however, conditional on ratings across different agencies concurring. When CRAs do not agree on their assessment of credit risk of the borrower, resulting in split ratings, the conflicting information fails to reduce uncertainty on borrower risk. Although there are other information sources available, credit ratings are the only source which require no investment by credit providers and are easily available to all banks in a syndicate. When uncertainty on the credit worthiness of a borrower remains largely unresolved due to split ratings, banks might require an additional premium to provide capital.

To that effect, in this paper we analyze the role of (un)certainty resulting from credit ratings in syndicated loan pricing. Banks that are not familiar with the borrower will be less likely, and less willing, to provide capital (Sufi, 2007) when it is difficult to correctly estimate the riskiness of a borrower, except at a higher price. We call this premium, which

is solely dependent on the level of uncertainty banks face when determining the credit risk of the borrower, the uncertainty premium.

Split ratings have been widely documented in the bond market, where research finds that approximately 13% of bond ratings are split at the letter level and 50% are split at the notch level. In our sample, 46% of borrowers with two ratings are split rated and of these 6% are split at the letter level. Morgan (2000) shows that disagreement between rating agencies can be an indication of information opacity of the borrower to the market. Livingston and Zhou (2010) find that information uncertainty, as proxied by split ratings, is priced by bond holders.

The effect of split ratings on bank loans is especially interesting, because bank loans offer an insight into dynamics not present in the bond market. We exploit the fact that we know who the providers of credit are, allowing us to study the effect of ratings in the presence of other information sources, such as creditor-debtor relationships and bank monitoring ability. This allows us to more accurately determine the weight of ratings in the pricing process, and the importance of ratings for bank loans.

We develop a theoretical framework, which demonstrates that the uncertainty in the riskiness of the firm will lead to banks charging an uncertainty premium to split rated firms. The theory also provides a rationale explaining why firms still opt for two ratings rather than one, despite the risk of split ratings. If borrowers believe their ratings will corroborate each other, obtaining a second rating would be optimal as it results in a discount relative to a single rating.

We empirically test the predictions of the theoretical model in the syndicated loan market. We start by investigating the question in the pooled cross-section, where we estimate the effect of split ratings on spreads. We also decompose the effect into different levels of uncertainty, as measured by the gap between ratings, led by the predictions of our model that the magnitude of the uncertainty premium is directly proportional to the degree of information uncertainty. We acknowledge that there are numerous potential sources of endogeneity. The main potential source is that rated firms may be fundamentally different from non-rated firms, for example they are bigger firms with larger loans. Additionally, some might argue that firms with two ratings are, in turn, different from firms with only one rating. We consider two complimentary strategies to deal with the potential endogeneity. First, we run all our specifications on both a sample of all firms, i.e. all firms with one rating and two ratings, and on a sub sample of only firms with two ratings. Second, we use a difference-in-difference (DD) approach to estimate the premium on loans of firms switching from two equal ratings to split ratings, and those switching from split ratings to two equal ratings. This allows us to more clearly provide evidence of a causal relationship, albeit on a much smaller sample.

The identity of credit providers is known in the syndicated loan market, and they can build a relationship with the borrower over successive loans, obtaining private information, and as a consequence potentially reducing the uncertainty they face. We can observe

the effect of relationship lending on the importance of third party information sources. Repeated borrower-lender transactions have been shown to lead to lower loan spreads with stronger effects when borrower transparency is low (Bharath, Dahiya, Saunders, and Srinivasan, 2011). We expect a strong borrower-lender relationship to reduce the uncertainty premium that split rated borrowers experience. Lead banks, which have repeatedly lent to the same borrowers, gather private information and will therefore have a stronger prior on the creditworthiness of the borrower. This private information will presumably decrease the importance of credit ratings for these particular borrowers. Consequently, we think split ratings will have a weaker effect on spreads when there is a borrower-lender relationship resulting from private information at these lenders' disposal. This private information will lead to lower uncertainty on the true underlying rating of the borrower.

Second, we can look at the structure of the syndicate to see whether or not a syndicate headed by a reputable lead arranger is better able to accumulate information and effectively communicate this information to syndicate members, thereby potentially making ratings less important. A syndicated loan is set up by the lead arranger, which in turn sells pieces of the loan to other participant banks. Lead arrangers sign a preliminary contract, 'mandate', where they provide the borrower with an amount they are willing to lend and a spread range, which also specifies collateral, covenants and fees. Lead arrangers proceed with the search for participant lenders. The effect of lead arranger reputation plays an important role in the syndicate formation, as reputation can reduce the problem of information asymmetry in a syndicate (Sufi, 2007). If a loan to a borrower is headed by a reputable bank, participant banks may deem credit ratings less important given the certification of quality that the reputable lead arranger represents. Participant banks will also factor in the information signaled by the reputable lead arranger, which might, in turn, make credit ratings and particularly split ratings, a less important factor in the pricing process. If a borrower has split ratings, implying that information about the borrower is ambiguous, lead arranger certification could potentially offset some of this uncertainty, resulting in a lower premium. Participant banks might shift their appraisal of the true underlying creditworthiness of a borrower if lead arranger certification weights heavily enough.

Finally, based on our theoretical model, as well as previous research, we expect the uncertainty premium to be increasing in the level of risk aversion. We examine whether the uncertainty premium is sensitive to the level of risk aversion in the market. We argue that banks will likely require a larger premium to lend to informationally risky borrowers during times of high risk aversion. We investigate this by looking at the uncertainty premium during the global financial crisis as defined by NBER. Next to looking at the global economic crisis, we also specifically control for the time-varying risk aversion in the market. Overall, our results show that banks do indeed care more about the informational uncertainty during high risk aversion periods, as evidenced by a higher required premium to lend to these borrowers during such times.

The rest of this paper is organized as followed. In section 3.2 we develop a theoretical model to determine the predictions we test with the empirical section. In section 3.3, we discuss the data we use followed by the methodology in section 3.4. Sections 3.5 and 3.6 present the empirical results and we conclude in section 3.7.

3.2 Theory

This section proposes a general theory on the uncertainty premium firms face based on their ratings. Our model is loosely based the model of Sharpe (1990). We consider three borrower types, H(igh), M(edium) and L(ow), where the type refers to their probability of success (or one minus probability of default) $P = [P_H \quad P_M \quad P_L]$, with $P_H > P_M > P_L$. For simplicity we will assume that $P_M = \frac{P_H+P_L}{2}$. For banks it is typically unknown of which type the firm is, and without any information, they have to base their loan pricing on population proportions θ_H, θ_M, and θ_L, which sum to one. Again, for simplicity assume an equal distribution, $\theta_q = 1/3$ for all q, i.e. $\theta = [\theta_H \quad \theta_M \quad \theta_L]' = [1/3 \quad 1/3 \quad 1/3]'$.

Banks use credit rating agencies to obtain information on borrower types. A bank updates its beliefs about the firm based on the attached rating, and shifts its assigned probabilities of firm type θ with the CRAs assessment ϕ, which is a vector with 1 on the type assessed by the CRA. We will assume a very strict updating rule, which can easily be relaxed at the cost of elegance. A single rating will update the beliefs to $\tilde{\theta} = \frac{\theta+\phi}{2}$. An additional rating from a different CRA may be requested to further update the beliefs to $\tilde{\theta} = \frac{\phi_1+\phi_2}{2}$,where ϕ_i denotes the rating of the first or second CRA.

In this set-up the bank's beliefs $\tilde{\theta}$ can have one of three forms. A single rating induces beliefs that are strongly favored toward one type, with a small probability of it being one of the others. A twice-rated firm with two equal ratings makes the banks certain the firm is of that type. However, when $\phi_1 \neq \phi_2$ the CRAs cannot agree, the firm obtains a split rating and the bank is still uncertain about the type of the firm. The beliefs are that the firm is one of two types with equal probability.

How should banks price these three types of beliefs? Here it should be noted that this induces two types of uncertainty, which we argue should both be priced. First, the loan is risky, as there is a non-zero probability of default. Next, the banks (potentially) face uncertainty on the firm's quality, and thus probability of default, and as such the utility derived from a loan provided at any given rate. To analyze the relative risk premia we analyze four examples. We consider a firm that has been issued an M rating by a single agency, such that $\tilde{\theta}_{\text{Single M Rating}} = [1/6 \quad 2/3 \quad 1/6]'$, a firm that's been issued two M ratings, such that $\tilde{\theta}_{\text{Two M Rating}} = [0 \quad 1 \quad 0]'$ and a firm that has been issued an L and a H rating, $\tilde{\theta}_{\text{Split L/H Rating}} = [1/2 \quad 0 \quad 1/2]'$.

3.2.1 No Risk Aversion

First consider the break-even rate when assuming no risk aversion for banks. At this loan rate, the gross cost of fund per unit loaned, $(1+\tilde{r})$ equals the bank's expected gross return (assuming zero recovery rate); r satisfies $(1+\tilde{r}) = p^e(1+r)$, where p^e is the bank's expected probability of success $p^e = \tilde{\theta}'P$. Note that for all four set-ups the assumptions imply that $p^e = \frac{P_H+P_L}{2}$. That is, a risk-neutral bank would treat all these firms equally, and set the rate to $r = \frac{\tilde{r}+1-p^e}{p^e}$. In the empirical section we will use controls such that firms have the same p^e conditional on observables to obtain a similar concept.

3.2.2 No Type Uncertainty

We now introduce risk aversion. The payoff of any given loan can be written as a lottery L_q with two states, success and failure, which have payoff 0 and $(1+r)$ with probabilities $(1-P_q)$ and P_q, respectively. The bank then faces a compound lottery $L_C(\tilde{\theta})$, which has lotteries L_q with probability $\tilde{\theta}_q$. So while the expected probability of success is equal, the probability of being in different states differs amongst all, so the bank faces different compound lotteries in each of the four scenarios.

We assume a simple utility function $U(W) = E(W) - \frac{\gamma}{2(1+\gamma)}Var(W)$, where W is the payoff of the unit investment, and γ is the coefficient of relative risk-aversion. The expected wealth of each lottery L_q equals $P_q(1+r)$. Their variance equals $P_q(1+r-P_q(1+r))^2 + (1-P_q)(0-P_q(1+r))^2 = (1+r)^2P_q(1-P_q)$, such that typically $Var(L_H) < Var(L_M) < Var(L_L)$ (as long as $P_L > 0.5$).

We can write down the utility of each of the three lotteries.

$$
\begin{aligned}
U(L_L) &= P_L(1+r) - \frac{\gamma}{2(1+\gamma)}(P_L)(1-P_L)(1+r)^2 \\
U(L_M) &= \frac{1}{2}(P_L+P_H)(1+r) - \frac{\gamma}{2(1+\gamma)}\left[\frac{1}{2}(P_H+P_L-P_HP_L) - \frac{1}{4}(P_H^2+P_L^2)\right](1+r)^2 \\
U(L_H) &= P_H(1+r) - \frac{\gamma}{2(1+\gamma)}(P_H)(1-P_H)(1+r)^2
\end{aligned}
\tag{3.1}
$$

It can easily be shown that, $U(L_L) < U(L_M) < U(L_H)$. Moreover, given $P_M = \frac{P_L+P_H}{2}$ and $P_L > 0.5$, we can write $U(L_M) - \frac{U(L_H)+U(L_L)}{2} = \frac{\gamma}{2(1+\gamma)}\left[\frac{1}{2}(P_HP_L) - \frac{1}{4}(P_H^2+P_L^2)\right](1+r)^2$, which is negative as long as $P_L < P_H$. In other words, $U(L_M) < \frac{U(L_H)+U(L_L)}{2}$.

To conclude, if the bank is certain of the type of firm, it will set the rates to their utility break even rate $U(1+\tilde{r}) = U(L_q)$, where $r_L > r_M > r_H$, which are the break even rates corresponding to each type as set in section 3.2.1.

3.2.3 Type Uncertainty

Now assume the bank is uncertain about the type of the firm, but it has beliefs, based on the CRA ratings, of $\tilde{\theta}$. The bank faces what is essentially a compound lottery and has to

set a rate to hedge in the possibility of the firm being of the lower type.

For any belief $\tilde{\theta}$, the expected utility equals

$$\mathbb{E}[U(L_C(\tilde{\theta}))] = \tilde{\theta}_L U(L_L) + \tilde{\theta}_M U(L_M) + \tilde{\theta}_H U(L_H),$$

and its variance equals

$$\begin{aligned} Var[U(L_C(\tilde{\theta}))] = \tilde{\theta}_L (U(L_L) - \mathbb{E}[U(L_C(\tilde{\theta}))])^2 \\ + \tilde{\theta}_M (U(L_M) - \mathbb{E}[U(L_C(\tilde{\theta}))])^2 \\ + \tilde{\theta}_H (U(L_H) - \mathbb{E}[U(L_C(\tilde{\theta}))])^2. \end{aligned}$$

Using the utility function U and the utility of each lottery (3.1), we can determine the ordering in utility of the three beliefs for a given rate r. We can then again, using the utility function U determine the expected utility. The expressions are rather complicated, but it can easily be shown that

$$U(L_c(\tilde{\theta}_{\text{Two nonsplit}}) > U(L_c(\tilde{\theta}_{\text{One rating}}) > U(L_c(\tilde{\theta}_{\text{Two Split}}) \tag{3.2}$$

As a direct consequence of this, the rates charged on the loan have an inverse relationship, with the split rating obtaining the highest premium.

Obtaining a rating gives a credible signal to the banks on the firm's quality. The reduction in uncertainty the bank faces is priced in the loan, and the firm gets a lower rate. The theory provides a reason for obtaining not just one, but two ratings. Two equal ratings further reduce uncertainty, which does not have to be priced by the bank, lowering the loan rate. However, when the second rating differs from the first, the uncertainty will lead the bank to charge a much higher premium.

3.3 Data

We obtain the data from Loan Pricing Corporation's DealScan, which contains detailed information on loan contract terms, lead arrangers, and participant lenders. According to DealScan, their data are primarily collected from Securities and Exchange Commission (SEC) filings. Our starting sample includes information on 110,641 completed loans issued between 1993 and 2014 where information on spreads is available. The data include the spread borrowers pay on their loans, the all in spread drawn (AISD), in addition to an expansive list of loan characteristics, syndicate information, and borrower information such as borrower name, industry, credit ratings and borrower sales. We start our analysis by investigating our question using only the data available in DealScan. Given that we are interested in the effect of credit ratings, and their differences, on loan spreads, DealScan provides us with the most important data to answer our question. This follows from Sufi (2007) and Asquith, Beatty, and Weber (2005) who argue that syndicated loans

often have pricing that is mainly dependent on the borrower's credit rating. We use senior secured issuer credit ratings at issuance from Moody's and S&P, which are the two most represented CRAs in general and in DealScan in particular. We transform the letter ratings into an ordinal scale ranging from 1 to 21, at the notch level, see Table 3.1. In general, ratings from Moody's and S&P are used interchangeably, therefore this transformation to an ordinal variable and the comparison should not represent a problem. In addition, in our sample ratings from the two agencies carry similar credit risk, as evidenced by similar spreads per rating class across agencies shown in Table 3.1. In order to be able to compare the ratings of borrowers, especially borrowers with more than one rating, we construct a measure of the average rating for each borrower when both Moody's and S&P are available. We do not find systematic differences in ratings between Moody's and S&P in our sample. The average of Moody's is 10.46, median is 10 and standard deviation is 4.44, while the average of S&P is 10.74, the median is 11 and the standard deviation is 4.21. More specifically, Table 3.1 shows the average rating per class per agency, and whether they are significantly different from each other. As the table shows, only 3 of the 21 classes show significant differences. This shows that in most instances ratings by Moody's and S&P are not significantly different from each other in our sample.

Next, we match Dealscan to Compustat in order to further control for borrower characteristics. This allows us to control for a multitude of firm financial information that have been shown to affect spreads. We control for firm, bank, and loan characteristics following previous literature, a detailed explanation of variables and their description can be found in Appendix A.

Descriptive statistics are shown in Table 3.2 for different samples, in order to compare across the different groups of interest. The first column shows the full dataset, that is, all observations for which AISD is non-missing and at least one rating is available. The second column shows the results for the sample of firms which have two available ratings, which are split. Finally, the third column shows the descriptives for borrowers which have two ratings, but are not split rated. The differences in spread for firms in these different groups is clear in this table. Firms with split ratings pay significantly higher spreads than firms with no split ratings, and firms with only one rating. This is in line with our theoretical model, which predicts that having a split rating leads to information uncertainty in the market that harms the borrower in the form of higher spreads. Importantly, differences for other variables across groups are not significant. Thus, on average, firms with split ratings are not fundamentally different from firms with no split ratings.

3.4 Estimating the effect of Split Ratings

The empirical methodology attempts to identify the causal effect of split ratings on the required risk premia in the form of loan spreads. The ideal situation to determine the

Table 3.1: Rating Conversion

This table presents the Moody's and S&P ratings and their transformation to an ordinal scale. The last column presents the p-values of the t-test on the paired spreads being equal. Significant differences are presented in bold.

	All rated firms			Twice rated firms			
Numerical Rating	Rating	Mean	St. Dev	Rating	Mean	St.Dev	p-value Difference
1	Aaa	38.491	79.233	AAA	40.417	66.764	0.762
2	Aa1	29.511	26.033	AA+	35.630	33.919	0.200
3	Aa2	50.775	90.351	AA	46.113	75.774	0.557
4	Aa3	42.587	74.266	AA-	41.308	67.068	0.797
5	A1	43.579	60.937	A+	45.980	53.901	0.453
6	A2	47.154	50.319	A	50.559	57.159	0.097
7	A3	59.401	54.818	A-	61.350	52.434	0.395
8	Baa1	82.987	67.668	BBB+	81.239	66.001	0.503
9	Baa2	100.448	69.758	BBB	101.492	70.760	0.647
10	Baa3	136.708	85.642	BBB-	134.252	83.283	0.406
11	Ba1	182.356	108.849	BB+	175.692	103.346	0.187
12	Ba2	208.653	113.096	BB	201.788	119.322	0.177
13	Ba3	271.301	148.332	BB-	249.284	132.428	**0.000**
14	B1	311.002	149.872	B+	295.052	145.013	**0.000**
15	B2	355.334	185.239	B	348.247	182.455	0.238
16	B3	327.994	163.894	B-	322.928	159.819	0.486
17	Caa1	377.061	180.014	CCC+	368.959	184.463	0.481
18	Caa2	399.988	190.158	CCC	381.455	188.150	0.359
19	Caa3	388.056	179.427	CCC-	389.773	200.498	0.956
20	Ca	455.278	242.482	CC/C	450.114	278.089	0.914
21	C	467.986	284.984	D	448.739	238.312	0.693

causal relation would be random assignment of split ratings to firms. If split ratings are randomly assigned, then the specification that estimates the causal effect of (split) ratings on outcome *Spread* of firm i would be:

$$Spread_i = \alpha + \beta \times SPLIT_i + \epsilon_i \tag{3.3}$$

With random assignment, the coefficient β represents the causal effect of having a split rating on outcome *Spread*. While this specification is indicative of the effect of split ratings, in reality, at least two factors limit the reliability of these results. First, some firms have only one rating, and as such, cannot have split ratings. Whether or not to get two ratings is a choice by the firms, and it is difficult to argue that the choice to obtain two ratings is not influenced by the possibility of having a split rating or not. Second, firms that obtain split ratings may be fundamentally different from firms that obtain two equal ratings and similarly, firms that obtain one rating might be fundamentally different from firms that obtain two ratings. In either situation we have to control for the possible endogeneity, as standard estimates of β are biased.

Our analysis therefore consists of two main specifications. First we consider a general cross-sectional setting in which we can use all loan information we have. Here, we can compare the pricing of loans to split rated borrowers with otherwise similar loans, controlling for a long list of characteristics such as the borrower's rating or the loan's

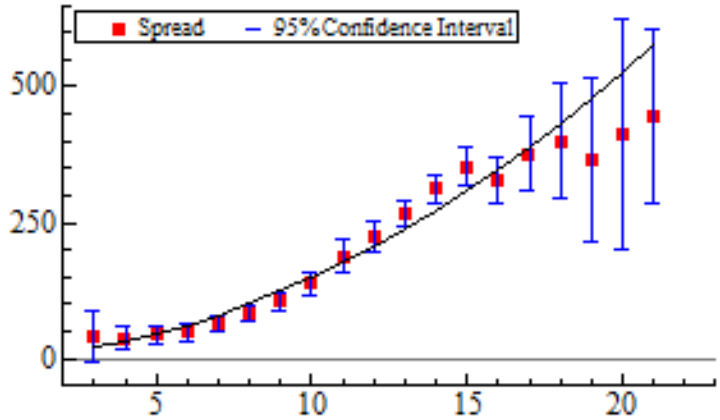
Table 3.2: Descriptive Statistics

This table presents summary statistics for variables from both DealScan and Compustat. The variables are presented for the maximum number of observations, where the dependent variable is not missing. *** indicates significant differences at the 1% level.

	All borrowers			Split rated borrowers			Non-split rated borrowers			Split - Non-Split
	N	mean	sd	N	mean	sd	N	mean	sd	
Borrower Characteristics										
AISD	46,361	205	157.1	17,171	227.5	162.2	11,264	182.9	152.6	44.6***
Log(loansize)	46,344	19.23	1.371	17,161	19.3	1.326	11,262	19.56	1.356	-0.26***
Log(borrower sales)	31,544	21.1	1.673	12,175	21.18	1.598	8,096	21.54	1.755	-0.36***
Average Ratings	46,367	11.44	3.906	17,173	11.98	3.682	11,265	10.62	3.927	1.36***
Leverage	17,358	0.551	0.115	7,177	0.556	0.115	5,125	0.539	0.113	0.017***
Profitability	20,102	0.113	0.0386	8,110	0.113	0.0378	5,740	0.117	0.0381	-0.004***
Size	20,841	8.862	2.246	8,326	8.787	2.141	6,002	9.048	1.986	-0.261***
Loan Characteristics										
Secured	26,498	0.73	0.444	10,803	0.755	0.43	6,230	0.622	0.485	0.133***
Covenant	42,799	0.43	0.495	15,870	0.502	0.5	10,367	0.478	0.5	0.024***
Termloan	46,365	0.366	0.482	17,172	0.394	0.489	11,265	0.317	0.465	0.077***
Senior	46,334	0.996	0.0617	17,160	0.996	0.0595	11,254	0.996	0.061	0.000
Bank Characteristics										
Relationship (Number)	46,367	0.159	0.198	17,173	0.165	0.198	11,265	0.176	0.2	-0.011***
Reputation (maximum)	44,355	0.102	0.999	16,578	0.144	0.982	10,910	0.229	0.983	-0.085***

Figure 3.1: Empirical Assumption

This graph shows spreads as a function of ratings. We make the economically motivated restriction to impose a polynomial relationship, which is supported by data as evidenced by this figure.



size and maturity etc. Second, we attempt to more clearly pin down the causal effect of obtaining a split rating by using a difference-in-difference (DD) setup. Transforming the DealScan data into a format such that we can estimate a DD results in a significant reduction of loans used for estimation, but allows us to estimate the causal effect, as we can specifically look at the premium firms have to pay on new loans when their ratings change from non-split to split and from split to non-split.

3.4.1 Ratings and spreads

Our methodology allows us to specifically see the effect of having a split rating relative to having a non-split rating. According to our theoretical model, when a borrower has a split rating, in a world with no information uncertainty and with no risk-aversion, the loan should be priced at the same rate as if the borrower would have the average of both ratings. However, in a world where information is priced very heavily, and where agents are risk averse, having a split rating will likely increase spreads as the banks will require an uncertainty premium relative to a loan of a borrower who has the average rating with certainty.

Hence, we define the cost of split ratings as the difference in spreads between a loan of a split-rated borrower, and an otherwise similar loan to an otherwise similar firm with a single rating or non-split two ratings with equal average as the split ratings. For example, when a borrower has two ratings, one of the value A and one of the value BBB, we want to compare its loan spread to loans of similar borrowers with an A- rating, which is equal to the average of the two ratings for the split rated borrower.

It is clear that the correct specification of the relation between ratings and spreads is vital to accurately measure the effect of split ratings. Since ratings are a discrete variable, the standard in the literature is to include rating dummies. For the analysis of

split ratings this leads to a problem. When a firm has a one-notch split, the average of the two ratings is in between two ratings and we cannot observe any non-split loans with equal average rating to compare them to. For this reason we opt for a specification in which we put the ratings on an ordinal scale instead (an overview is provided in Table 3.1), and include the average rating and its square term in a regression set-up. Figure 3.1 shows the relationship between spread and ratings, which in turn also justifies our choice for a polynomial relationship. This choice has two advantages. First, we easily solve the problem of one-notch splits. Second, for some of the lower ratings very few observations are available, such that a dummy set-up would not always lead to higher spreads for lower ratings. This is stricly a small sample issue, as evidenced by the larger confidence bounds. Imposing the polynomial relationship essentially amounts to imposing the economic constraint that this should be the case.[1]

3.4.2 Cross-sectional analysis

First we estimate the difference in spreads between loans to split-rated borrowers and otherwise similar loans to non-split rated borrowers. To that effect we consider the following baseline specification

$$Spread_i = \alpha + \beta_1 SPLIT_i + \beta_2 AverageRating_i + \beta_3 AverageRating_i^2 + \beta' \mathbf{x}_i + \epsilon_i, \quad (3.4)$$

where $SPLIT_i$ is a dummy variable that takes the value of 1 if the borrower has a split rating, and $\mathbf{x}$ is a vector of control variables at the loan, borrower, and bank level. The coefficient of the $SPLIT_i$ variable can be interpreted as the difference between the actual spread and the estimated spread if both ratings would have been the same. If spreads on split rated loans are determined by the average of the two ratings available, then the coefficient on $SPLIT_i$ should be zero. If however, lenders view split ratings as information uncertainty and require an uncertainty premium, then we expect to find a positive and significant coefficient on $SPLIT_i$. All specifications throughout the paper have clustered standard errors at the borrower level to take cross-sectional correlations of different loans to the same borrowers into account.

As a first step towards dealing with the potential endogeneity of firms that are rated twice versus those that are only rated by one CRA, we present results for all specifications using both the full sample of all rated firms, i.e. those rated by both CRAs and those only rated by one, and a sub-sample of only firms with two ratings. The main results are reported in Table 3.3. Specifications (1) and (2) concern the full sample, i.e. borrowers

[1] Livingston and Zhou (2010) provide an alternative methodology to deal with the one-notch split ratings while using rating dummies. They use two regression specifications where first, the superior rating of a split rated borrower is taken as the rating to that particular borrower, and in a second specification the inferior rating is used. By taking a weighted average of the two results a split-premium can be estimated as well. For robustness we include these results in a later section. See Appendix A for details.

Table 3.3: Cross-Sectional Analysis

This table presents the results for the cross-sectional analysis. The dependent variable is spread in basis points. The SPLIT variable takes the value of one if the borrower has split ratings and zero otherwise. A positive coefficient implies that the bank requires a premium above the spread that corresponds to non-split rated borrower with the same average rating. The control variables include loan and firm level characteristics. The regressions also include year, industry, and country fixed effects. Standard errors are clustered at the firm level. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	All rated firms		Twice rated firms	
	(1)	(2)	(3)	(4)
Borrower Characteristics				
SPLIT	14.56***	16.37***	4.927*	10.09***
	(2.272)	(3.004)	(2.592)	(3.353)
Average Rating	11.02***	7.339***	11.55***	9.381***
	(1.930)	(2.448)	(2.417)	(3.006)
Average Rating^2	0.418***	0.529***	0.423***	0.509***
	(0.0876)	(0.119)	(0.114)	(0.145)
Leverage		55.62***		40.80**
		(16.49)		(20.11)
Profitability		-111.0**		-83.37
		(46.04)		(52.94)
Size	0.693	3.136**	-0.492	3.074*
	(0.955)	(1.306)	(1.192)	(1.578)
Loan Characteristics				
Multiple Tranches	14.07***	12.30***	15.58***	12.11***
	(2.233)	(2.954)	(2.676)	(3.476)
Termloan	55.16***	46.08***	53.66***	44.05***
	(2.222)	(3.080)	(2.642)	(3.417)
Secured	37.54***	42.11***	39.33***	42.72***
	(3.250)	(4.377)	(4.097)	(5.312)
Covenant	-25.01***	-5.017	-30.80***	-10.59**
	(2.888)	(4.108)	(3.823)	(5.229)
Libor base	-22.12***	-22.25***	-15.35***	-15.97**
	(3.871)	(6.054)	(4.868)	(7.615)
Loan size	-11.00***	-11.85***	-10.69***	-10.91***
	(1.065)	(1.575)	(1.348)	(1.895)
Maturity	-8.169***	-13.08***	-9.654***	-14.57***
	(2.026)	(2.371)	(2.366)	(2.774)
Constant	202.9***	171.4***	229.6***	153.7***
	(24.97)	(38.21)	(31.64)	(44.84)
Observations	13,835	6,099	9,126	4,449
Adjusted R-squared	0.551	0.586	0.573	0.604
Purpose	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

with both one and two ratings, and (3) and (4) are the same specifications for firms rated by both CRAs only. (1) and (3) only have control variables provided by DealScan while the other two specifications show results including firm specific control variables retrieved from Compustat. The table shows that after controlling for a large variety of spread determinants, split rated firms pay between 5 and 16 basis points higher spreads than non-split rated firms. The table also shows that, as expected, the lower the rating, i.e. the higher the credit risk, the higher the spread. This relationship is non-linear as evidenced by the positively significant coefficient on the square term of average rating. Note that the coefficient size difference between the two samples, i.e. all firms with ratings and firms with two ratings only, is exactly what we expect to see. According to our model, any single rated firm is likely to obtain a lower second rating. Therefore, the spread we observe for single rated firms is lower than it should be, biasing downward the estimated spread per rating and inflating the SPLIT premium. In addition we see that borrowers with higher leverage will have significantly higher spreads, this is also expected given that a higher leverage means that a borrower is riskier. For the loan characteristics we see that spreads are higher on loans where the deal has multiple sub-deals, when the loan is a term loan, and when the loan is secured. In contrast, having financial covenants, having Libor as the base rate, having larger loans and a longer maturity all lead to lower spreads.

3.4.2.1 Difference-in-Difference

Next we consider the Difference-in-Difference set-up. We use the general specification

$$Spread_{ist} = \alpha + \gamma_s Treated_s + \delta D_{st} + \lambda_t + x_{ist} + \epsilon_{ist}, \tag{3.5}$$

where $D_{st} \equiv Split_s \times d_t$ a dummy variable which equals one for the borrower with split ratings during the time period where it is 'treated', and λ_t are year dummies.

In order to be able to estimate this model we have to transform the DealScan database into a panel. We proceed as follows. We set up a panel at a yearly frequency[2], where we take the largest loan provided to borrower i within year t as the observation for that firm's year. This results in an unbalanced panel with roughly 1500 year-firm observations.

Next we have to determine the treatment and control groups. We consider two analyses here, firms that go from non-split ratings to split ratings and the reverse, those that go from split ratings to non-split ratings. For the former, we define the Treated sample as any firm that during our sample at any point changes from having two equal ratings to having two unequal ratings. The relevant elements in the D_{st} matrix are set to 1 starting from the non-split-year until the split reverses and the ratings are unequal. As a control group, we consider all firms that have two equal ratings throughout the sample. For the latter analysis we have the exact reverse situation.

[2]The results are similar when we consider half-yearly or two-yearly periods.

Table 3.4: Difference-in-Difference

This table presents the results for the difference-in-difference analysis. We define the treatment as a firm that has switched from being non-split to split, or vice versa. Correspondingly, the control group is a firm which has been non-split throughout the entire sample, and the reverse. The dependent variable is spread in basis points. The control variables include loan and firm level characteristics. The regressions also include year, industry, and country fixed effects. Standard errors are clustered at the firm level. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Borrower Characteristics				
Treatment non-split to split	10.52**	13.18**		
	(4.882)	(6.450)		
Control for non-split to split	-6.125	-4.182		
	(5.282)	(9.000)		
Treatment split to non-split			-11.72**	-18.67***
			(5.843)	(6.771)
Control for split to non-split			-5.425	-1.970
			(4.468)	(6.350)
Average Rating	17.53***	19.36***	27.24***	21.80***
	(3.878)	(5.194)	(3.600)	(4.739)
Average Rating^2	-0.0654	-0.0958	-0.550***	-0.326
	(0.176)	(0.230)	(0.149)	(0.202)
Constant	-9.939	-69.59	-30.05	-243.6***
	(61.85)	(80.20)	(53.19)	(75.22)
Observations	1,110	575	1,503	708
Adjusted R-squared	0.696	0.694	0.623	0.661
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
Firm Characteristics	No	Yes	No	Yes
Borrower Size	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

Table 3.4 contains the results of the difference-in-difference analysis. Specifications (1) and (2) consider the non-split to split treatment, while (3) and (4) report the results of the reverse. For both specifications we see that there is no significant difference in spreads between the treated and non-treated firms, apart from the effect of changing from non-split to split ratings or the reverse. The coefficients on the variable Treatment non-split to split shows a positive and significant effect on the spread of these borrowers. The effect is economically significant, ranging from 11 to 14 basis points. These results show that when a borrower switches from being non-split rated to being split rated, he will face significantly higher costs of borrowing. This shows the causal effect of split ratings on

the spreads banks demand from borrowers. Specifications (3) and (4) show the results for borrowers that switch from having split ratings to having equal ratings from both CRAs. These results are again in line with the results show above. A borrower will benefit from significantly lower spreads, between 12 and 20 basis points lower on average, if and when he switches from having split ratings to having non-split ratings. The results of our DD approach show that the analysis performed above is capturing the effect of ratings on spread, given that the magnitude and the signs of the coefficients are both in line and very similar to those reported above.

3.4.3 The role of split magnitude

All split ratings are not equal. Basic risk-aversion theory dictates that the larger the uncertainty the higher the required risk premium. As such one would expect that a one-notch split would require a smaller premium than a two- or three-notch split. Indeed, out of the almost 11,000 loans for which we have two ratings, nearly 7,000 are split. Over 6,000 of those are one or two notches apart, and only 1% of the differences is more than three notches. We investigate these dynamics in Table 3.5. The general specifications are the same as in Table 3.3, with the only difference that the $SPLIT_i$ dummy is split up into the number of notch-differences. Specifically, we consider one-, two- and three-notch splits, and bundle all splits larger than three into the four-notch+ variable in order to obtain a reasonable amount of observations. The table shows that across specifications, the split-premium is increasing in the magnitude of the split. The results are mostly significant, except in specification (3), and in general there is an increasing trend in the premium for larger splits. These results also give us some insight into the risk aversion of the average bank. For example, specification four shows that banks charge split rated borrowers approximately 7 basis points higher spreads on their loans relative to non-split rated borrowers. Similarly, borrowers with two-notch splits have 11 basis points higher spreads than those with one notch difference, and those with three notch splits have 22 basis points higher spreads than those with two-notch splits. The results coincide with our expectation that the larger the split, the larger the premium banks demand. Four splits or more lead to a premium of 40 basis points to split rated borrowers, which is both economically and statistically significant.

Table 3.5: Notch Level Split Ratings

This table presents the results for the cross-sectional analysis at the notch level. The difference between the Moody's and the S&P rating for each borrower is calculated and a dummy variable captures the effect of a split size. The dependent variable is spread in basis points. The control variables include loan and firms level characteristics. The regressions also include year, industry, and country fixed effects. Standard errors are clustered at the firm level. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	All rated firms		Twice rated firms	
	(1)	(2)	(3)	(4)
Borrower Characteristics				
SPLIT one	12.67***	12.48***	3.452	6.804*
	(2.491)	(3.200)	(2.732)	(3.529)
SPLIT two	13.42***	17.23***	3.528	11.31**
	(3.880)	(4.793)	(4.192)	(5.221)
SPLIT three	17.97**	29.47***	8.252	22.26**
	(7.553)	(10.18)	(7.702)	(10.02)
SPLIT four+	43.13***	49.56***	32.46***	39.76**
	(10.32)	(15.81)	(10.39)	(15.54)
Average Rating	11.25***	7.473***	12.08***	9.656***
	(1.939)	(2.441)	(2.434)	(2.999)
Average Rating^2	0.404***	0.515***	0.392***	0.485***
	(0.0879)	(0.118)	(0.115)	(0.144)
Leverage		55.23***		40.87**
		(16.39)		(19.90)
Profitability		-107.8**		-80.09
		(46.06)		(53.14)
Size	0.555	2.961**	-0.704	2.837*
	(0.951)	(1.305)	(1.186)	(1.575)
Loan Characteristics				
Multiple Tranches	14.08***	11.99***	15.60***	11.74***
	(2.234)	(2.949)	(2.677)	(3.469)
Termloan	55.11***	45.99***	53.56***	43.92***
	(2.221)	(3.072)	(2.636)	(3.410)
Secured	37.16***	41.33***	38.95***	41.83***
	(3.223)	(4.340)	(4.045)	(5.270)
Covenant	-25.13***	-4.856	-31.02***	-10.48**
	(2.883)	(4.057)	(3.814)	(5.162)
Libor Base	-22.49***	-22.37***	-15.87***	-16.07**
	(3.860)	(5.955)	(4.855)	(7.499)
Loan size	-11.00***	-12.08***	-10.67***	-11.20***
	(1.065)	(1.578)	(1.348)	(1.898)
Maturity	-8.028***	-12.92***	-9.389***	-14.36***
	(2.010)	(2.353)	(2.332)	(2.749)
Constant	205.4***	180.1***	231.8***	164.3***
	(24.95)	(38.01)	(31.58)	(44.71)
Observations	13,835	6,099	9,126	4,449
Adjusted R-squared	0.552	0.588	0.574	0.606
Purpose	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

3.5 Further Predictions

3.5.1 The role of risk-aversion

The previous results show that banks significantly price the uncertainty resulting from split ratings. The magnitude of the premium banks demand is a function of their risk aversion. In order to specifically test the effect of risk aversion on spreads, we look at spreads and the split premium in times of higher risk aversion. We start by comparing split premia in periods of economic down-turns to split-premia in good economic times. We investigate the effect of economic crises by looking at the global economic crisis of 2008, as defined by the NBER. Investigating the crisis is of great interest as the crisis drove debates on whether or not the rating agencies were doing their job. As such, ratings were already seen as troublesome and led to less credible information. This intensifies the scrutiny on ratings, and increases the importance of a joint signal from the rating agencies to retain some credibility. Therefore a split rating is expected to be of larger consequence during the crisis than in any other period. In addition, and in order to more accurately proxy for risk aversion in certain periods, we control for time-varying risk aversion, proxied by the measure of Brandt and Wang (2003). The measure allows time-variation in risk aversion as a response to news about aggregate consumption growth and inflation.[3] This last measure allows us to more specifically test for the risk aversion in the market at any particular point in time. The results are reported in Tables 3.7.

3.5.1.1 Global financial crisis

To proxy for the global financial crisis we use the NBER definition dates to determine when the US (where the majority of our loans originate) was in recession and include an interaction term between recession dummy and SPLIT. We do not include the main recession effect, because we are controlling for year fixed effects across all specifications. Table 3.6 shows the results for the global financial crisis. The interaction term Crisis $\times$ SPLIT shows the effect of having a split rating during poor economics times on spreads. The positive significant coefficient shows that banks do indeed charge split rated borrowers higher spreads during poor economic times. The magnitude ranges from 24 basis points to 30 basis points. These differences are both economically and statistically significant. Following the reasoning that risk aversion is higher during poor economic times, these results provide some support to the hypothesis that banks are risk averse institutions, leading banks to require higher premia.

[3]For a detailed explanation of how the measure is constructed, see Bams, Honarvar, and Lehnert (2015); Brandt and Wang (2003). We thank Iman Honarvar Gheysary for providing us with his estimates.

3.5.1.2 Time-varying market risk aversion

Next, in order to more precisely tackle risk aversion we consider the time-series of market risk aversion as in Brandt and Wang (2003). Brandt and Wang (2003) find that risk aversion varies with inflation and aggregate consumption. We specifically control for the level of risk aversion, in addition to the crises periods, because it has been shown that there need not be a crisis for risk aversion to be high. This measure captures the level of risk aversion on a more granular level. The results can be seen in Table 3.7. We take the time varying risk aversion measure and standardize it by demeaning and dividing by standard deviation. This allows for an easy to interpret coefficient. Table 3.7 shows the results of risk aversion at any point in time on spreads to split rated borrowers. The coefficient on the variable Risk Aversion × SPLIT shows the effect of risk aversion to split rated borrowers. The positively significant coefficient across all specifications shows that during times of high risk aversion, the average bank will charge a split rated borrower a higher premium than during other times. Specifically, a one standard deviation increase in risk aversion leads to an additional uncertainty premium of approximately 24 to 28 basis points, again, both economically and statistically significant, as shown in Table 3.7.

These results are in line with our hypothesis that banks are risk averse institutions and that the uncertainty due to split ratings is priced by banks. The results using the market risk aversion also reinforce the results found using poor economic times. In general, our results show that indeed, during poor economic times and in times of high risk aversion, banks require higher premia from split rated borrowers than they do in normal economic times, and in times when risk aversion is low.

3.5.2 The role of leadarrangers

Bank loans allow for repeated interactions between borrowers and lenders which can, in turn, affect the loan terms borrowers obtain. Bank-borrower relationships provide lenders with the opportunity to obtain additional information about borrowers, potentially not identified by CRAs. Through their relationship, banks might be better able to determine the true underlying "rating" of a borrower and determine whether a split rated borrower is closer to the superior or the inferior rating, in turn making credit ratings less important to these banks. Therefore, we expect to observe a smaller premium on loans to split rated borrowers where a bank-borrower relationship exists.

The reputation of lead arrangers can also play an important role in the information dissemination process, and the trust that other banks in the syndicate place on the information provided by a particular lead arranger. We hypothesize that more reputable lead arrangers are better able to convince participant banks of the private information they have on a borrower, leading to lower spreads on loans to firms whose syndicate is headed by a reputable lead arranger.

Table 3.6: Split Ratings in Crises Periods

This table presents the results for the cross-sectional analysis. The dependent variable is spread in basis points. The SPLIT variable takes the value of one if the borrower has split ratings and zero otherwise. A positive coefficient implies that the bank requires a premium above the spread that corresponds to non-split rated borrower with the same average rating. We also include a dummy variable for the global financial crisis interacted with split to determine whether premias are higher during periods of high risk aversion. The control variables include loan and firm level characteristics. The regressions also include year, industry, and country fixed effects. Standard errors are clustered at the firm level. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	All rated firms		Twice rated firms	
	(1)	(2)	(3)	(4)
Borrower Characteristics				
SPLIT	13.42***	15.23***	3.680	8.928***
	(2.272)	(3.030)	(2.593)	(3.383)
Crisis × SPLIT	30.84***	25.07*	31.98***	24.02*
	(10.69)	(13.18)	(10.58)	(12.99)
Average Rating	11.12***	7.461***	11.82***	9.597***
	(1.925)	(2.441)	(2.408)	(2.989)
Average Rating^2	0.412***	0.522***	0.407***	0.496***
	(0.0872)	(0.118)	(0.113)	(0.144)
Leverage		56.70***		42.47**
		(16.30)		(19.76)
Profitability		-106.9**		-78.68
		(46.23)		(53.27)
Size	0.543	3.018**	-0.732	2.904*
	(0.954)	(1.305)	(1.187)	(1.572)
Loan Characteristics				
Multiple Tranches	14.33***	12.58***	15.98***	12.45***
	(2.237)	(2.957)	(2.673)	(3.477)
Termloan	55.13***	45.98***	53.60***	43.90***
	(2.223)	(3.089)	(2.645)	(3.433)
Secured	37.32***	41.93***	39.02***	42.53***
	(3.246)	(4.379)	(4.093)	(5.317)
Covenant	-24.94***	-4.942	-30.70***	-10.57**
	(2.889)	(4.109)	(3.819)	(5.228)
Libor Base	-21.89***	-22.07***	-14.90***	-15.62**
	(3.845)	(5.995)	(4.809)	(7.529)
Loan size	-11.02***	-11.88***	-10.72***	-10.94***
	(1.065)	(1.576)	(1.347)	(1.895)
Maturity	-7.850***	-12.78***	-9.150***	-14.19***
	(2.011)	(2.336)	(2.331)	(2.732)
Constant	204.5***	171.4***	231.8***	153.9***
	(24.94)	(38.22)	(31.63)	(44.84)
Observations	13,835	6,099	9,126	4,449
Adjusted R-squared	0.552	0.587	0.574	0.605
Purpose	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

Table 3.7: Risk Aversion

This table presents the results for the cross-sectional analysis. The dependent variable is spread in basis points. The SPLIT variable takes the value of one if the borrower has split ratings and zero otherwise. A positive coefficient implies that the bank requires a premium above the spread that corresponds to non-split rated borrower with the same average rating. Risk Aversion*SPLIT shows whether banks charge split rated borrowers higher premias during periods of high risk aversion. Market risk aversion is measured following Brandt and Wang (2003). The control variables include loan and firm level characteristics. The regressions also include year, industry, and country fixed effects. Standard errors are clustered at the firm level. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	All rated firms		Twice rated firms	
	(1)	(2)	(3)	(4)
Borrower Characteristics				
SPLIT	20.64***	20.62***	10.37***	13.66***
	(2.336)	(3.038)	(2.623)	(3.375)
Risk Aversion × SPLIT	26.95***	24.99***	28.38***	25.46***
	(2.049)	(2.650)	(2.073)	(2.700)
Average Rating	10.77***	7.161***	11.19***	9.198***
	(1.949)	(2.444)	(2.436)	(2.982)
Average Rating^2	0.419***	0.519***	0.420***	0.487***
	(0.0873)	(0.118)	(0.113)	(0.141)
Leverage		68.05***		58.56***
		(15.94)		(19.23)
Profitability		-92.87**		-64.42
		(45.20)		(51.46)
Size	-0.585	2.184*	-2.540**	1.672
	(0.937)	(1.265)	(1.142)	(1.493)
Loan Characteristics				
Multiple Tranches	13.73***	11.84***	14.73***	11.21***
	(2.194)	(2.902)	(2.582)	(3.401)
Termloan	55.68***	47.04***	54.32***	45.34***
	(2.205)	(3.084)	(2.586)	(3.422)
Secured	35.40***	40.51***	36.18***	41.05***
	(3.165)	(4.308)	(3.911)	(5.171)
Covenant	-22.46***	-2.390	-26.24***	-6.681
	(2.863)	(3.981)	(3.756)	(4.990)
Libor Base	-21.04***	-21.75***	-14.00***	-14.70**
	(3.797)	(5.722)	(4.661)	(6.966)
Loan size	-11.82***	-13.11***	-12.02***	-12.67***
	(1.048)	(1.560)	(1.299)	(1.873)
Maturity	-7.710***	-12.79***	-8.738***	-13.96***
	(2.015)	(2.346)	(2.311)	(2.728)
Constant	247.1***	208.4***	300.9***	207.5***
	(25.07)	(37.98)	(31.64)	(44.20)
Observations	13,835	6,099	9,126	4,449
Adjusted R-squared	0.564	0.602	0.594	0.625
Purpose	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

3.5.2.1 Borrower - Lender Relationship

Theoretically, information uncertainty decreases with the amount of information accumulated on a specific borrower. Relationship lending involves customer-specific information gathered over time through multiple interactions (Boot, 2000). The more frequently a borrower has borrowed from a lender, the less important ratings will be, due to information accumulated over the span of the relationship. This, in turn, means that when there is an established borrower-lender relationship, split ratings will have a smaller effect on spread than in the absence of such a relationship. Previous research has show that borrower-lender relationships do indeed lead to better loan terms (Bharath, Dahiya, Saunders, and Srinivasan, 2011; Sufi, 2007). We control for borrower-lender relationship using a dummy variable, relationship (dummy), which takes the value of one if the borrower has had the particular lead arranger in a previous syndicate in the past five years. The results are shown in Table 3.8. We also construct this variable for a period of three years and one year, but the results stay relatively stable across the different measures.

Specifications (1) through (4) show the results for the full sample of borrowers rated both once and twice. Specifications (1) and (2) include only a proxy for relationship and in specifications (3) and (4) we also interact relationship with SPLIT. We do this in order to see whether relationship banking is more important to split rated borrowers than to non-split rated borrowers. Specifications (5) through (8) include the same specifications, but on the sample of borrowers only rated twice.

Borrower-lender relationships do indeed lead to lower premia, as evidenced by the significantly negative coefficients, ranging from approximately -6 to -10 basis points across all specifications. The interaction term is however, not significantly different from zero. Implying that repeated interactions do not offer a higher benefit to split rated borrowers relative to other borrowers. An established borrower-lender relationship is evidently beneficial to all borrowers. A potential explanation for the fact that relationships do not lead to reductions in split premia, but do lead to reductions in the general level is as follows. When banks face a new potential borrower, they have to incur large costs in acquiring information, reducing uncertainty, and establishing terms of loans. For any subsequent loan, this investment is no longer necessary to the same extent, and spreads on loans are reduced. This, however, does not take away the fact that these borrowers are split rated. Banks will do everything they can to resolve the uncertainty for the first loan. Repeated interaction is not going to reduce the uncertainty about creditworthiness.

3.5.2.2 Lead arranger reputation

The structure of the syndicated loan market allows for situations in which credit ratings are potentially less important. Loans are headed by lead arrangers, and previous research has shown that lead arranger reputation can significantly mitigate information problems in the syndicate (Chemmanur and Fulghieri, 1994; Demiroglu and James, 2010; Jones, Lang,

Table 3.8: Borrower-Lender Relationship

This table presents the results for the cross-sectional analysis. The dependent variable is spread in basis points. The SPLIT variable takes the value of one if the borrower has split ratings and zero otherwise. A positive coefficient implies that the bank requires a premium above the spread that corresponds to non-split rated borrower with the same average rating. Relationship is a dummy variable which takes the value of one if the borrower-lender pair has happened before in the previous five years. The control variables include loan and firm level characteristics. The regressions also include year, industry, and country fixed effects. Standard errors are clustered at the firm level. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	All rated firms				Twice rated firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Borrower Characteristics								
SPLIT	10.49***	12.89***	11.26***	15.02***	2.110	7.575***	1.398	7.321*
	(1.774)	(2.512)	(2.289)	(3.470)	(2.099)	(2.849)	(2.797)	(4.147)
Relationship × SPLIT			-1.776	-4.204			1.569	0.480
			(3.073)	(4.305)			(3.625)	(4.891)
Average Rating	17.06***	13.23***	17.06***	13.31***	16.85***	15.24***	16.82***	15.23***
	(1.645)	(2.004)	(1.645)	(1.995)	(2.145)	(2.633)	(2.144)	(2.629)
Average Rating^2	-0.0460	0.0955	-0.0461	0.0928	-0.0170	0.0440	-0.0160	0.0446
	(0.0652)	(0.0857)	(0.0652)	(0.0853)	(0.0876)	(0.112)	(0.0876)	(0.112)
Leverage		63.79***		63.85***		52.01***		51.99***
		(12.38)		(12.37)		(14.70)		(14.71)
Profitability		-139.6***		-139.1***		-105.6***		-105.7***
		(35.54)		(35.50)		(40.86)		(40.87)
Size	-1.714**	0.356	-1.709**	0.369	-2.665***	0.00139	-2.667***	-0.000804
	(0.772)	(1.182)	(0.772)	(1.181)	(0.947)	(1.342)	(0.947)	(1.343)
Loan Characteristics								
Multiple Tranches	20.35***	21.12***	20.33***	21.05***	20.16***	18.47***	20.16***	18.48***
	(1.828)	(2.502)	(1.830)	(2.508)	(2.182)	(2.877)	(2.183)	(2.881)
Termloan	39.58***	36.45***	39.59***	36.47***	39.14***	35.50***	39.13***	35.49***
	(1.620)	(2.302)	(1.620)	(2.304)	(1.936)	(2.626)	(1.935)	(2.626)
Secured	45.70***	47.59***	45.70***	47.58***	49.50***	51.15***	49.48***	51.14***
	(3.035)	(4.038)	(3.034)	(4.038)	(3.885)	(4.875)	(3.885)	(4.874)
Covenant	-14.19***	0.470	-14.18***	0.440	-15.89***	-2.245	-15.89***	-2.238
	(2.191)	(3.312)	(2.191)	(3.315)	(2.832)	(3.910)	(2.832)	(3.910)
Libor Base	-20.43***	-19.80***	-20.48***	-19.90***	-17.00***	-19.05***	-16.94***	-19.02***
	(3.564)	(5.496)	(3.571)	(5.522)	(4.452)	(6.410)	(4.451)	(6.412)
Loan size	-9.682***	-10.45***	-9.690***	-10.45***	-9.146***	-9.069***	-9.145***	-9.071***
	(0.836)	(1.327)	(0.836)	(1.329)	(1.039)	(1.549)	(1.039)	(1.549)
Maturity	-2.994*	-8.949***	-2.998*	-8.927***	-4.164**	-9.617***	-4.161**	-9.617***
	(1.591)	(1.962)	(1.591)	(1.965)	(1.824)	(2.224)	(1.825)	(2.224)
Bank Characteristics								
Relationship	-8.522***	-7.798***	-7.772***	-5.847*	-8.957***	-9.670***	-9.955***	-9.976**
	(1.627)	(2.380)	(2.067)	(3.046)	(1.940)	(2.776)	(2.895)	(4.022)
Constant	187.6***	168.8***	187.3***	166.9***	205.9***	147.1***	206.5***	147.5***
	(20.97)	(32.62)	(20.96)	(32.60)	(25.95)	(38.52)	(25.95)	(38.62)
Observations	13,835	6,099	13,835	6,099	9,126	4,449	9,126	4,449
Adjusted R-squared	0.629	0.654	0.629	0.654	0.659	0.674	0.659	0.674
Purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower	borrower	borrower	borrower	borrower

Table 3.9: Lead Arranger Reputation

This table presents the results for the cross-sectional analysis. The dependent variable is spread in basis points. The SPLIT variable takes the value of one if the borrower has split ratings and zero otherwise. A positive coefficient implies that the bank requires a premium above the spread that corresponds to non-split rated borrower with the same average rating. The variable for lead bank reputation (Reputation) measured as the market share of a lead arranger in particular year based on loans originated in that specific year. The control variables include loan and firm level characteristics. The regressions also include year, industry, and country fixed effects. Standard errors are clustered at the firm level. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	All rated firms				Twice rated firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Borrower Characteristics								
SPLIT	10.22***	12.71***	11.73***	15.72***	2.154	6.674**	2.330	9.403**
	(1.819)	(2.585)	(2.088)	(3.105)	(2.173)	(2.961)	(2.569)	(3.797)
SPLIT × Reputation			-2.698*	-4.514**			-0.271	-3.544
			(1.578)	(2.281)			(1.810)	(2.493)
Average Rating	17.55***	14.29***	17.57***	14.45***	16.88***	15.88***	16.89***	16.09***
	(1.755)	(2.143)	(1.746)	(2.111)	(2.278)	(2.812)	(2.278)	(2.779)
Average Rating^2	-0.0635	0.0552	-0.0639	0.0483	-0.0218	0.0157	-0.0223	0.00667
	(0.0688)	(0.0903)	(0.0685)	(0.0891)	(0.0924)	(0.118)	(0.0924)	(0.117)
Leverage		66.73***		67.17***		54.41***		55.14***
		(12.75)		(12.74)		(15.22)		(15.26)
Profitability		-139.7***		-140.9***		-108.2**		-109.4***
		(36.31)		(36.30)		(42.05)		(41.98)
Size	-1.339	0.746	-1.368*	0.733	-2.169**	0.338	-2.175**	0.292
	(0.814)	(1.242)	(0.813)	(1.240)	(0.998)	(1.421)	(0.999)	(1.420)
Loan Characteristics								
Multiple Tranches	21.50***	22.35***	21.43***	22.18***	21.17***	19.67***	21.17***	19.56***
	(1.908)	(2.615)	(1.908)	(2.616)	(2.275)	(3.032)	(2.275)	(3.030)
Termloan	39.90***	36.47***	39.89***	36.43***	39.36***	35.68***	39.37***	35.68***
	(1.661)	(2.348)	(1.661)	(2.349)	(1.983)	(2.685)	(1.983)	(2.685)
Secured	44.85***	45.94***	44.84***	45.98***	49.38***	50.21***	49.39***	50.22***
	(3.173)	(4.235)	(3.169)	(4.223)	(4.046)	(5.105)	(4.045)	(5.102)
Covenant	-14.15***	0.700	-14.19***	0.748	-14.83***	-1.511	-14.83***	-1.424
	(2.281)	(3.447)	(2.281)	(3.441)	(2.901)	(3.966)	(2.902)	(3.975)
Libor Base	-20.44***	-21.78***	-20.40***	-21.60***	-17.32***	-20.25***	-17.31***	-20.42***
	(3.980)	(6.040)	(3.965)	(5.991)	(4.754)	(6.701)	(4.752)	(6.692)
Loan size	-9.236***	-9.791***	-9.262***	-9.765***	-8.902***	-8.700***	-8.900***	-8.607***
	(0.869)	(1.354)	(0.869)	(1.352)	(1.075)	(1.599)	(1.074)	(1.590)
Maturity	-2.957*	-9.653***	-2.970*	-9.635***	-4.061**	-10.21***	-4.062**	-10.22***
	(1.698)	(2.088)	(1.700)	(2.092)	(1.946)	(2.355)	(1.947)	(2.363)
Bank Characteristics								
Reputation	-5.006***	-5.221***	-3.799***	-3.099*	-5.546***	-5.898***	-5.368***	-3.618*
	(0.911)	(1.283)	(1.167)	(1.679)	(1.075)	(1.504)	(1.559)	(2.121)
Constant	167.0***	142.2***	167.5***	139.7***	188.8***	129.7***	188.7***	125.6***
	(22.61)	(34.35)	(22.60)	(34.38)	(28.17)	(41.78)	(28.16)	(41.72)
Observations	12,991	5,754	12,991	5,754	8,644	4,203	8,644	4,203
Adjusted R-squared	0.626	0.649	0.626	0.650	0.656	0.670	0.656	0.670
Purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower	borrower	borrower	borrower	borrower

and Nigro, 2005; Lin, Ma, Malatesta, and Xuan, 2012; Sufi, 2007). We hypothesize that lead arranger reputation might be able to, at least to some extent, offset the informational uncertainty caused by split ratings. Lenders could take the presence of a reputable lead arranger as a sign of quality of either the borrower, or of the monitoring that the lender can provide. As a result, they might deem credit ratings in general, and split ratings in particular, less important in the pricing process. That is, lenders might place more emphasis on the signal a reputable lead arranger provides, in terms of credit risk of a borrower, than on the information uncertainty induced by split ratings. We specifically test for the effect a reputable lead arranger has on spreads to loans with split rated borrowers.

Table 3.9 shows the results for lead arranger reputation. We proxy for lead arranger reputation using the market share of each lead arranger per year (see e.g. Sufi (2007), Ross (2010) and Lin, Ma, Malatesta, and Xuan (2012)).[4] We do this using the universe of loans signed in a particular year, and not canceled, and calculate for each lender the market share per year based on all loans signed in that year. For ease of interpretation, we standardize the reputation variable by demeaning it and dividing it by its standard deviation.

Similar to the approach above, we start by looking at the sample with borrowers rated both once and twice in specifications (1) through (4). Specifications (1) and (2) include only a control for lead arranger reputation, which we confirm to have a significant effect on loan spreads (similar to e.g. Sufi (2007)). Specifications (3) and (4) include both a proxy for lead arranger reputation and an interaction term between lead arranger reputation and SPLIT. Similar to our argument on borrower-lender relationships, we include an interaction term in order to determine whether the mitigating effect of a reputable lead arrangers is stronger for borrowers with uncertainty. The coefficient on reputation can be interpreted as the sensitivity to a one standard deviation change in reputation, and as expected, it has a negative effect.

The coefficient on SPLIT, which can now be interpreted as the premium on a loan to a split rated borrower with a lead arranger with average reputation, is still significant and of equal magnitude as the results reported before.

Specifications (3) and (4) and (7) and (8) include the interaction effect. In specifications (3) and (4) we see an increase in the coefficient of SPLIT relative to the other specifications. In addition, we see that the interaction of SPLIT and lead arranger reputation is significantly negative. As such, it appears that lead arranger selection might offer a mitigating factor in the uncertainty premium. More reputable lead arrangers are potentially better able to credibly signal the quality of a borrower to participant banks, resulting in a decreased effect of the uncertainty stemming from credit rating agencies

[4]The underlying intuition is that banks can only obtain a large market share by means of reputable behavior, as the syndicated loan market is one of repeated interactions. If banks undercut competitors, or lead a loan with terms at odds with the creditworthiness of the borrower, other banks will refuse cooperation in future syndicates.

alone. Specifications (7) and (8) have similar results, although, SPLIT is not significant in specification (7) and the interaction term between SPLIT and reputation is not significant in either specification for the sample of borrowers rated twice only.

3.6 Robustness

As mentioned above, our main specifications are based on an ordinal variable for ratings as illustrated in Table 3.1. In this section, we show results for split ratings using the methodology of Livingston and Zhou (2010), where instead of using an ordinal variable to control for the ratings, we construct a dummy variable for each rating notch. The SPLIT rating is largely similar to the one used in our main specifications. However, in this section, there are two different models. In the inferior model, a borrower with split ratings will have both ratings replaced by the lower of the two, which in turn means that the SPLIT coefficient captures the premium or discount on a loan to a borrower for having a second, higher, rating. For the superior model, the process is simply reversed, the rating variable is replaced with the best of the two ratings, and the SPLIT reflects the premium/discount associated with the lower rating. An exact and detailed explanation of the methodology can be found in appendix B. This methodology also enables us to see whether banks only judge the quality of split rated borrowers based on their inferior or superior ratings. For example, if banks were to judge rated borrower based only on the lower of the two ratings, then we would expect SPLIT to be equal to zero. If however, SPLIT is different from zero, banks look at both ratings when determining loan prices.

Tables 3.10 and 3.11 show the results for this methodology. We control for all firm and loan level characteristics as in the specifications above. SPLIT has a positive significant coefficient in Table 3.10. This result means that, on average, a borrower with a second rating, which is worse than the rating we are controlling for, has approximately 20 basis points higher spreads on his loan. Similarly, Table 3.11 shows negative and significant coefficients on the variable SPLIT. This, in turn, shows that a borrower with a second rating, which is better than the rating we are controlling for, has on average between 10 to 13 basis points lower spreads on his loan.

In order to quantify the net effect of having a split rating, we need to take the difference between the coefficients for SPLIT in the inferior and the superior model. If we take specification one as an example, the net effect would be (19.85 - 13.48)/2 = 3.185 and for specification four this would be (21.36 - 10.01)/2 = 5.675. These results reinforce our main results and show that banks require a split premium from borrowers with split ratings to compensate them for the information uncertainty.

An alternative option is to only consider even-notch splits such that a corresponding loan with the average rating always exists. We consider this analysis in Table 3.12, where we restrict the sample to exclude those firms whose ratings differ by an odd number of splits. This restriction implies that we can observe loans to firms whose rating is exactly

Table 3.10: Superior Model

This table measures the effect of split ratings on spread following Livingston and Zhou (2010). We use two regression specifications. The first takes the superior rating as the actual rating for a split rated borrower and the second takes the inferior rating as the actual rating for a split rated borrower. Dummy variables are constructed for each notch rating. This table represents the Superior model. The dummy variable takes the value of one for the highest of the two ratings on a split rated borrower. We take a weighted average of the two results (Superior and Inferior Model) and the difference between these two allows us to determine the split-premium. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	All rated firms		Twice rated firms	
	(1)	(2)	(3)	(4)
SPLIT	19.85***	19.39***	19.47***	21.36***
(Relative to highest)	(2.092)	(2.659)	(2.366)	(3.075)
Aa1	-20.07	-10.69	-12.41	-28.97
	(15.67)	(29.18)	(16.79)	(37.43)
Aa2	3.255	11.48	-6.666	-7.907
	(8.967)	(13.61)	(13.17)	(16.80)
Aa3	4.397	1.404	2.743	-16.05
	(10.07)	(13.42)	(12.74)	(15.00)
A1	10.75	6.176	10.20	-0.818
	(8.075)	(10.20)	(11.52)	(13.05)
A2	13.23*	16.11	14.42	14.10
	(7.863)	(10.65)	(11.15)	(13.30)
A3	24.56***	21.82**	26.43**	17.35
	(7.547)	(9.770)	(10.86)	(12.59)
⋮	⋮	⋮	⋮	⋮
Caa1	244.3***	211.8***	256.1***	219.0***
	(12.21)	(16.37)	(16.26)	(19.99)
Caa2	254.1***	257.8***	263.1***	263.5***
	(16.09)	(27.70)	(23.05)	(33.67)
Caa3	246.0***	259.6***	268.7***	262.1***
	(18.84)	(22.78)	(25.92)	(24.78)
Ca	272.7***	265.4***	266.1***	274.4***
	(29.68)	(43.17)	(42.69)	(60.94)
C	312.8***	311.1***	221.9***	238.7***
	(17.67)	(31.47)	(42.92)	(21.48)
Constant	365.2***	278.3***	305.8***	184.6***
	(26.21)	(41.67)	(43.24)	(47.59)
Observations	13,835	6,099	9,126	4,449
Adjusted R-squared	0.617	0.668	0.637	0.683
Purpose	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
Firm Characteristics	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

Table 3.11: Inferior Model

This table measures the effect of split ratings on spread following Livingston and Zhou (2010). We use two regression specifications. The first takes the superior rating as the actual rating for a split rated borrower and the second takes the inferior rating as the actual rating for a split rated borrower. Dummy variables are constructed for each notch rating. This table represents the Inferior model. The dummy variable takes the value of one for the lowest of the two ratings on a split rated borrower. We take a weighted average of the two results (Superior and Inferior Model) and the difference between these two allows us to determine the split-premium. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	All rated firms		Twice rated firms	
	(1)	(2)	(3)	(4)
SPLIT	-13.48***	-11.13***	-13.34***	-10.01***
(Relative to lowest)	(2.201)	(2.674)	(2.435)	(3.007)
Aa1	-3.536	7.567	3.114	5.676
	(10.02)	(15.91)	(12.49)	(16.51)
Aa2	19.09*	25.04*	28.73*	4.571
	(11.30)	(13.65)	(17.45)	(17.63)
Aa3	9.059	21.85	6.642	4.983
	(12.40)	(17.76)	(13.81)	(22.24)
A1	14.67	15.63	16.31	8.734
	(10.30)	(10.18)	(11.69)	(13.49)
A2	17.26*	19.59*	20.19*	15.01
	(9.471)	(10.08)	(10.81)	(13.18)
A3	26.12***	28.01***	29.20***	23.55*
	(9.442)	(9.493)	(10.71)	(12.78)
⋮	⋮	⋮	⋮	⋮
Caa1	237.9***	230.4***	249.5***	241.3***
	(11.48)	(13.26)	(12.80)	(16.33)
Caa2	260.6***	256.1***	275.5***	263.6***
	(14.34)	(19.95)	(16.99)	(23.64)
Caa3	296.3***	288.1***	337.4***	315.6***
	(20.90)	(27.04)	(24.73)	(31.48)
Ca	277.3***	286.9***	277.2***	294.3***
	(21.31)	(31.24)	(23.84)	(39.53)
C	302.3***	298.0***	294.2***	292.6***
	(15.39)	(23.97)	(19.79)	(26.95)
Constant	376.9***	298.6***	322.1***	220.1***
	(26.51)	(41.13)	(39.33)	(44.71)
Observations	13,835	6,099	9,126	4,449
Adjusted R-squared	0.621	0.675	0.644	0.691
Purpose	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
Firm Characteristics	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	borrower	borrower	borrower	borrower

Table 3.12: Even-numbered Notch Splits

This table presents the results for the cross-sectional analysis restricted to non-split and even-numbered notch splits. The dependent variable is spread in basis points. The SPLIT variable takes the value of one if the borrower has split ratings and zero otherwise. A positive coefficient implies that the bank requires a premium above the spread that corresponds to non-split rated borrower with the same average rating. Specification (1) uses an ordinal variable to model the relationship between ratings and spreads, while specification (2) uses rating fixed effects. The control variables include loan and firm level characteristics. The regressions also include year, industry, and country fixed effects. Standard errors are clustered at the firm level. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
Borrower Characteristics		
SPLIT	21.11***	20.91***
	(5.459)	(5.485)
Average Rating	11.49***	
	(2.950)	
Average Rating^2	0.317**	
	(0.138)	
Leverage	22.03	14.70
	(21.88)	(22.05)
Profitability	-116.4**	-109.0*
	(56.76)	(56.45)
Size	6.154***	6.773***
	(1.926)	(1.922)
Loan Characteristics		
Multiple Tranches	6.902*	7.206*
	(4.019)	(4.014)
Termloan	52.33***	51.51***
	(4.644)	(4.587)
Secured	43.82***	36.00***
	(6.208)	(8.058)
Covenant	-8.543	-8.024
	(5.613)	(5.534)
Libor Base	-21.80***	-22.02***
	(7.336)	(6.815)
Loan size	-14.38***	-14.44***
	(2.174)	(2.180)
Maturity	-11.75***	-12.59***
	(3.181)	(3.156)
Constant	162.7***	205.2***
	(51.32)	(50.00)
Observations	4,007	4,007
Adjusted R-squared	0.518	0.522
Purpose	Yes	Yes
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Country Fixed Effects	Yes	Yes
Rating Fixed Effects	No	Yes
Clustered SE	borrower	borrower

equal to the average of all split ratings, such that we can model the relationship between ratings and spreads with fixed effects. Specification 1 repeats the usual specification which uses the ordinal rating scale on the restricted sample, while specification 2 uses the rating fixed effects. The split premium remains economically and statistically significant across both specifications, and is even higher than the one estimated in our main specifications of Table 3.3.

3.7 Conclusion

Credit ratings play an important in financial markets. They are the dominant source of information, which both lenders and investors use as a decision rule in determining the credit quality of firms. Consequently, credit rating agencies possess a significant influence in determining the cost of financing. CRAs have often been criticized however, because their rating methodology is a black box. They maintain complete discretion in their approach to analyze and determine the letter rating of a borrower. This represents a potential problem, particularly when the assessment of a borrower differs among CRAs. Credit ratings place firms in a category, which in turn, conveys the credit risk. When borrowers are placed in two different categories, credit ratings fail to properly inform users of the credit risk of a borrower.

We investigate this uncertainty in the bank loan market. Specifically, we argue that when banks are uncertain about the credit rating of a borrower, they will only be willing to provide capital at a higher rate. Banks price a loan according to the risk a borrower represents, when the risk is ambiguous to determine, banks will require a premium. We call this the split premium.

We develop a theoretical model which shows that a borrower with two ratings, which are the same, is a bank's ideal situation, as the lender can, with almost complete certainty, place the borrower in a credit risk category. However, when the ratings are split, lenders cannot know with certainty which rating is the true underlying rating of a borrower, and will only provide capital at a higher cost.

We test our theoretical predictions in a empirical setting. We start with a standard cross-sectional study, where we show that having a split rating, after controlling for firm and loan characteristics, leads to a split premium of between 5 and 17 basis points, depending on the specification. We also show a causal relationship, through a Difference-in-Difference approach. Results show that borrowers switching from being non-split rated to being split rated, experience a premium of between 11 to 13 basis points. Accordingly, borrowers switching from non-split to split rated experience a discount of between 12 to 19 basis points. We also show that the split premium is increasing in the size of the split, i.e. the level of uncertainty. Next, we show that during times of high risk aversion, banks require higher premia than during normal times. The premia banks charge are both statistically and economically significant. On average, split rated borrowers

have approximately 5% higher spreads than non-split rated borrowers, which amounts to approximately a quarter of a million dollars per year in additional interest payments.

Some might argue that given the risk averse nature of banks, they will always be conservative and price the loans based on the lowest rating a borrower has. Our results show that this is not the case. When borrowers are split rated, banks will looks at both ratings to determine the credit risk of borrowers.

The syndicated bank loan market allows us to study other mechanisms at work which could, potentially, mitigate the effects of split ratings on spread. These mechanisms are primarily bank-borrower relationships and lead arranger reputation. Both of which make information gathering and/or information dissemination easier or better in the syndicate. We find that relationship lending is equally important to all borrowers, and it is not more important for split rated borrowers than for other borrowers. In contrast, having a reputable lead arranger appears to be more important for split rated borrowers than for non-split rated borrowers. One potential explanation is that reputable lead arrangers have a certification effect, which dominates credit ratings. We show that split rated borrowers with syndicates headed by reputable lead arrangers experience an additional discount, above the average reputable lead arranger, of up to 5%.

Appendix A: Variable Definitions

Variable	Units	Definition	Source
All-in-spread-drawn	basis points	Total spread paid over LIBOR on each dollar drawn down from the loan net of upfront fees	DealScan
Senior	dummy	One if the loan is senior and zero otherwise	DealScan
Secured	dummy	One if the loan is secured and zero otherwise	DealScan
Multiple Tranches	dummy	One if there are multiple loans within a deal and zero otherwise	DealScan
Termloan	dummy	One if the loan type is a termloan and zero otherwise	DealScan
Covenant	dummy	One if the loan has a financial covenant in place and zero otherwise	DealScan
Loan size		Natural logarithm of loan size in US dollars	DealScan
Maturity		Natural logarithm of months to loan maturity	DealScan
Size		Natural logarithm of borrower sales in US dollars	DealScan
Leverage		Shows the level of leverage for the borrower in the previous year. Calculated as (lct + dltt) / at	Compustat
Profitability		Shows earnings of the borrower in the previous year. Calculated as: ebitda / at	Compustat
Reputation		The maximum market share of all lead arrangers in a syndicate. Market share is calculated using the universe of loans signed and not canceled in the preceding year. For ease of interpretation, the variable is standardized to have zero mean and unit variance.	DealScan
Relationship (Dummy)		One if the borrower has had the particular lead arranger in a previous syndicate in the past five years. For cases in which there are multiple lead arrangers, the variable takes unity if at least one of the lead arrangers has led a syndicate to the borrower in the past five years.	DealScan

Appendix B: Methodology

An alternative methodology to quantify the effect of split ratings on spread is explained in this section. We use two regression models to estimate the impact of split ratings on bank loans. In the first model, we evaluate the spreads on loans with split ratings against those with non-split ratings with superior ratings. That is, when a loan a has split rating, we use the higher of the two ratings, the superior rating, to construct the rating variable. The split rating dummy variable therefore reflects that this borrower has an inferior rating not captured by the rating variable. The superior rating model is as follows:

$$Spread_i = \alpha + \beta_{sup} SPLIT_i + \beta_2 SuperiorRating_i + \mathbf{x}_i + \epsilon_i \tag{3.6}$$

SPLIT is a dummy variable that takes a value of 1 if the borrower has a split rating. SuperiorRating is the rating variable, where 1 is the highest possible rating (AAA) and 21 is the lowest possible rating (D), and $\mathbf{x}$ is a vector of control variables. If the spreads on split rated loans are determined by the superior rating alone, then the second rating should have no impact and β_{sup} should be insignificant. Alternatively, if the second rating does matter to banks, and the inferior rating is also taken into consideration, then the inferior rating should increase spreads and β_{sup} should be positive and significant. Therefore, the coefficient of the SPLIT variable can be interpreted as the difference between the actual spread and the estimated spread if both ratings would have been the same.

In the second regression model we reverse the procedure. We evaluate the spreads for loans based on the inferior of the two ratings. That is, for split rated borrowers, we use the lower of the two ratings in the construction of the rating variable. Here, the SPLIT dummy variable reflects the fact that the split rated loan has an inferior rating not captured by the rating variable. This inferior rating model is as follows:

$$Spread_i = \alpha + \beta_{inf} SPLIT_i + \beta_2 InferiorRating_i + \mathbf{x}_i + \epsilon_i \tag{3.7}$$

The variables are defined in the same way as the superior model except that the lower of the two ratings is used to construct the rating variable. In the inferior model the coefficient for $SPLIT_i$, β_{inf}, can also be interpreted as the difference between the actual loan spread and the estimated spread if both ratings would have been the same at the highest of the two ratings.

The final step required to determine the net effect of split ratings on spreads is to take the difference between the coefficient of SPLIT for the superior model and the inferior model, i.e. β_{sup} and β_{inf}.

Chapter 4

Interconnectedness Through Syndication: Market Awareness and Reactions*

4.1 Introduction

The most important channels through which banks are linked are the interbank deposit market, deposit interest rate risk, and through syndicated lending De Vries (2005). Indeed, lending money to borrowers constitutes the core business of banks and syndicated loans are a large part of this core business. Syndicated lending represents the largest source of US corporate financing (Sufi, 2007), and it shows no signs of slowing down. Worldwide, syndicated lending reached an 11-year high of approximately US$5.28 trillion in 2018, having recovered from the shock of the financial crisis (Dealogic, 2019; Reuters, 2018).

A syndicated loan is a loan provided to a borrower by at least two lenders jointly. Banks repeatedly cooperate on syndicated loans arranged by one another. One of the primary motives for the risk sharing is the promise of risk reduction through diversification, because each bank only holds a portion of a loan, as opposed to the whole loan. Syndication therefore provides the lender with the possibility to hold a diversified portfolio of small exposures to many different loans. For the borrowers, it means access to a larger pool of capital. At first glance, the resulting networks of banks seems beneficial, for both the lender and the borrower.

Although there are many positive aspects to syndicated lending, the resulting downsides are often overlooked. In particular, through the common exposures the banks now face on their asset side, a sufficiently large (potentially local) shock, may bring down part of the financial sector (Acharya and Yorulmazer, 2008). In this paper we investigate whether these negative externalities of syndication are incorporated into asset prices by financial markets. Our focus is on the connections that arise between the balance sheets

*The data used in this chapter is supplied by Erasmus University Rotterdam, the current affiliation of the author.

of banks because of syndicated loans. While the diversification effect leads to reduced risk, the common exposures to default risk lead to increased common, or systemic, risk. We use the network of syndicated loans to assess the degree of balance sheet commonality between individual banks to proxy the re-distribution, rather than reduction, of risk through syndication. We investigate whether participants in the equity and CDS markets react to the level, or changes, in the degree of bank-specific interconnectedness through syndicated loans. While the probability of a systemic breakdown is low, the magnitude of the losses associated with such events may be sufficient to require a risk premium (Kelly and Jiang, 2014). Conversely, market participants may deem the probability of a large enough shock happening to be too small and therefore ignore the risk, or they may believe the probability of a bailout to be very high, also resulting in them ignoring the risk.

We find that both equity and CDS markets appear to require a risk premium for the systemic interconnectedness of firms as proxied by their common exposures in the syndicated loan market. The risk premia are not constant over time. Indeed, in line with the above, it appears that before the financial crisis of 2008 market participants deemed the probability of a systemic event too small, or a bailout too likely, to require a risk premium. After the demise of Lehman Brothers in September 2008, markets appear to react to the level and changes of syndication-driven interconnectedness. It appears the Lehman collapse made the market aware of the risk inherent in the joint operations of financial institutions, causing the market to pay more attention to it. This argument is in line with Chen (1999), who shows that negative information about failing banks in the economy leads to a reassessment of risks of other similar banks in the economy.

Our analysis is therefore two-fold. First, based on the findings of Dumontaux and Pop (2013) and Ivashina and Scharfstein (2010a), that the shock coming from the bankruptcy of Lehman affected other financial institutions negatively, we investigate whether the commonality of the syndicated loan portfolio between individual banks and Lehman drives heterogeneity in market reactions on individual banks around Lehman's bankruptcy. Similar to Iyer and Peydro (2011) and Ivashina and Scharfstein (2010a), we find that both the effect on equity returns and CDS prices was stronger for banks whose loan portfolio was strongly interconnected with that of Lehman.

Second, we investigate whether markets react to changes in the syndication driven interconnectedness in normal times as well. While a market reaction to a large system-wide event such as the collapse of Lehman Brothers is perhaps not entirely surprising, we also find that investors appear to monitor small, apparently minute changes, in the syndicated loan market. We show that markets react negatively to the signing of syndicated loans that strongly increase the lead arrangers' interconnectedness, while there is no market reaction to the signing of a typical loan, or of an interconnectedness decreasing loan. Similarly, we find that CDS spreads are higher for those banks that are central to the syndicated loan market, with banks with high interconnectedness having higher spreads, whilst controlling for the usual risk characteristics of the banks.

Our paper is related to at least three streams of literature. First, and most importantly, we provide empirical evidence related to a largely theoretical literature on the effects of diversification on the risk profile of financial institutions and the financial system. We build on a large body of theoretical work on the negative aspects of diversification. Ibragimov, Jaffee, and Walden (2011) show that financial institutions' actions to diversify, which are optimal for individual banks, may prove to be suboptimal for society. Similarly, De Vries (2005) demonstrates that the potential for systemic breakdowns is strong if asset returns have fatter tails than the normal distribution, which is an empirical regularity supported by ample evidence see e.g. (Gabaix and Ibragimov, 2011; Jansen and De Vries, 1991). Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), study the extent of financial contagion resulting from the structure of interbank liabilities. Their model predicts that diversification is mostly beneficial for small shocks, as the resulting system is less prone to contagious defaults. However, for sufficiently large shocks, highly diversified lending patterns facilitate financial contagion and create a more fragile system. The authors provide support for the hypothesis of Haldane (2009), that a highly interconnected financial system may be "robust, yet fragile". Acharya and Yorulmazer (2008) develop a model that shows how asset-side correlations, i.e. joint exposures to loans, can lead to joint asset side systemic risk through information contagion. More recently, Allen, Babus, and Carletti (2012) show that clustered asset structures lead to higher systemic risk when bad news about banks' future solvency circulates in the economy. Elliott, Golub, and Jackson (2014) develop a model that demonstrates that cross-holdings of debt lead to cascading failures. Cabrales, Gottardi, and Vega-Redondo (2017) explicitly study the trade-offs between the benefits of risk-sharing and the costs of contagion, akin to the diversification and interconnectedness trade-off the syndicated loan market faces. They find that the optimal level of risk-sharing is limited in case risk exposures are not globally convex, which is generally the case for fat-tailed distributions.

Few empirical papers have focused on the downside of syndicated lending and the trade-offs between the costs and benefits associated with it. Our paper is most closely related to Cai, Eidam, Saunders, and Steffen (2018), who were the first to explicitly recognize and measure the systemic potential associated with syndicated lending. They investigate the interconnectedness in the form of common risks among financial institutions by examining banks' exposure to large syndicated loans. They find positive and significant correlation between their interconnectedness measure and various systemic risk measures including SRISK (Brownlees and Engle, 2016), CoVaR (Adrian and Brunnermeier, 2016), and DIP (Black, Correa, Huang, and Zhou, 2016; Huang, Zhou, and Zhu, 2009, 2012).[1] While diversification means that the frequency of individual bank failures

[1]All these measures are based on stock market returns and publicly available accounting data. The syndicated loan market is decidedly less transparent. The SRISK as the expected capital shortfall of a financial institution conditional on prolonged market downturn. It is measured based on the size of a firm, its leverage, and its expected equity loss given economic distress. The ΔCoVaR is the difference between the VaR of the market conditional on a firm being in distress and the market's VaR when the

is significantly decreased, if defaults do start to occur and shocks are large enough, the sector as a whole is more vulnerable to systemic breakdowns. The authors also show that, consistent with theory, interconnectedness amplifies systemic risk during recessions. Their results highlight that bank-specific risk reduction through diversification ignores the negative externalities of an interconnected financial system.

Second, our paper adds to the literature on the relationship between systemic risk and equity returns. This stream of literature includes studies investigating the effects of failures of large financial institutions on the performance of the surviving institutions (e.g. Aharony and Swary, 1983; Dumontaux and Pop, 2013), and, Lang and Stulz (1992), who show that on average, bankruptcy announcements decrease the value of the firm's competitors and this effect is stronger for firms more highly correlated with the bankrupt firm. More broadly, this paper is also related to the literature on the pricing of risk and bad news in financial markets see e.g. Docking, Hirschey, and Jones (1997). Generally, these papers provide evidence for market discipline and show that investors make informed decisions when pricing assets, rather than being driven by panic.

In the context of financial contagion, Iyer and Peydro (2011) find that it is higher for banks with larger interbank exposure to the failing bank, as well as for those with weaker fundamentals. Dumontaux and Pop (2013) study the stock market reaction to Lehman's failure, and find that the biggest firms, those that hold crucial positions in the system, were most affected by Lehman's demise. Similar to this paper, Gasbarro, Le, Schwebach, and Zumwalt (2004) investigate stock market reactions to syndicated loan announcements. They focus on the borrower, rather than the lender, and find that loan announcements generate a positive wealth effect for the borrowing firm.

Our study adds to this literature by focusing on changes in systemic risk before it materializes. More specifically, we estimate the effects of loan announcements on lead-arranger stock prices, as a function of whether the loans in- or decrease the systemic risk inherent in the firm's portfolio. We find that loans that significantly increase the lead arranger's interconnectedness are met with a strong negative abnormal return of about 0.3% following the announcement of the loan. For loans with no effect on interconnectedness, or a diminishing effect, we don't observe a similar response. Investors view these loans as part of the ongoing business of the bank.

Finally, we add to the literature on Credit Default Swaps (CDS) pricing. A CDS can be seen as a bet on an institution's health and the price reflects the probability that the institution will not repay its debt in full (Hart and Zingales, 2010). The idea is that an increase in systemic risk in the financial sector should, in turn, lead to a greater risk of default for each individual institution within the sector. This should result in an increase in the average CDS spread (Giglio et al., 2011). Importantly, one can argue that CDS spreads are a better indicator of risk than equity, because equity also captures upside

firm is at its median. The DIP is the risk neutral expectation of the loss conditional on the loss exceeding a given threshold.

potential, and therefore might underestimate the probability of default in very volatile assets.

Indeed, Chiaramonte and Casu (2013) confirm that bank CDS spreads reflect the risk captured by bank balance sheet ratios and are therefore a good proxy for general bank risk. They find that the relationship between bank CDS spreads and balance sheet ratios is particularly tight during crises periods and post-crises periods. Similarly, Annaert, De Ceuster, Van Roy, and Vespro (2013) show that during the 2004-2006 period, changes in CDS spreads were mainly dominated by credit risk drivers. However, in the period preceding the crisis, their model virtually breaks down and economically sensible variables hardly seem to explain variation in CDS spreads. Interestingly, during financial crises, it is clear that credit risk drivers alone cannot explain changes in CDS spreads. They find that liquidity and the overall perception of bank stability become important in explaining significant parts of their variation.

To that end, we investigate whether the market sees the bank's level of interconnectedness resulting from syndicated lending as a serious driver of credit risk. By exploiting the cross-sectional and time variation in the levels of interconnectedness, we find that CDS spreads are significantly influenced by the level of interconnectedness, after controlling for a wide range of firm specific and market wide controls. The effect of interconnectedness on the spread increases substantially after the failure of Lehman.

The remainder of the paper is structured as follows. Section 4.2 explains how we compute the firm-specific, syndicated loan market based measure of interconnectedness, based on a methodology of Cai, Eidam, Saunders, and Steffen (2018). Section 4.3 discusses the data. Sections 4.4 and 4.5 present results of our analysis on equity and CDS data respectively. Finally, Section 4.6 concludes.

4.2 Interconnectedness and the Syndicated Loan Market

The syndicated loan market is one of the primary channels through which bank performance is correlated (Cai, Eidam, Saunders, and Steffen, 2018; De Vries, 2005). While most attention for the syndicated loan market has focused on the potential diversification benefits, few have addressed or investigated the negative externalities of banks' syndication. Indeed, if banks tend to work together with the same partner banks for the majority of deals, diversification effects are limited, and from a credit risk perspective, the two banks start to behave as one. As a result, during severe downturns, failure of a single institution may result into a system-wide crisis. Accordingly, syndication may lead to increased systemic risk.

Cai, Eidam, Saunders, and Steffen (2018) were one of the first to empirically study the syndication network with a view on systemic crises. They propose a measure of bank interconnectedness that is based on loan portfolio similarity using a large dataset of

syndicated loans. They study the cross-sectional properties of these interconnectedness risk measures and find that they are strongly correlated to, but are distinct from, some of the popular systemic risk measures in the literature, such as the SRISK measure of Brownlees and Engle (2016), which is an equity-based measure that computes how much capital would be needed to keep a bank from failing in the event of a large market downturn.

Rather than taking their measure as a general proxy for systemic risk, we take the measure more literally and argue that it measures the risk banks face through their syndicated loan portfolio in the event of extreme downturns. We then ask the question of whether market participants react to changes in the portfolio composition, or in other words, price the network-risk inherent in the syndicated loan portfolios of these banks.

We start by briefly recapping the interconnectedness measure of Cai, Eidam, Saunders, and Steffen (2018). In essence, their measure simply computes the similarity in loan portfolios by comparing their industry exposures. As with most distance measures, there is a trade-off between granularity and information. The granularity of the data allows us to construct this measure by taking the dollar exposure a bank has to each individual borrowing firm. However, if firm performance is correlated, such a measure will understate the practical implications of the overlap. If bank A has exposure to firm x, and none to firm y, with bank B having the opposite exposure, a simple distance measure will make these risks seem uncorrelated. If firm x and y tend to default at the same time, the actual commonality of the risk is understated. Cai, Eidam, Saunders, and Steffen (2018) therefore suggest to compute similarity in industry exposures rather than individual firm exposure. Specifically, they look at the areas banks are most heavily invested in by classifying their borrowers into industries based on 2-digit SIC codes. They subsequently compute the distance between two banks by quantifying the similarity of their total industry exposures.

The detailed construction of their measure is as follows. For each month during the sample period, we compute each lead arranger's total loan facility amount originated in the prior 12 months.[2] In case a loan has multiple lead arrangers, the loan amount is distributed according to the actual lending shares if available, and equally distributed if no data is available.

We then compute portfolio weights for each lead arranger $i = 1, ..., N$, in each specialization category $j = 1, ..., J$ (i.e. 2-digit SIC industry). Define $w_{i,j,t}$ as the weight lead arranger i invests in specialization j within the 12 months prior to month t. The weight is computed as the loan amount bank i lent as a lead-arranger to firms in industry j during months $t - 12$ to $t - 1$, divided by the total loan amount of that same lead-arranger over that time window.

[2]We only consider the lead arrangers for several reasons. First, lead arrangers hold larger fractions of loans than participant banks (Ivashina and Scharfstein, 2010b). Second, lead arrangers are more likely to keep the loans on their balance sheet (Benmelech, Dlugosz, and Ivashina, 2012), rather than selling it on the secondary loan market.

Next, for each month t, the distance between two banks, m and n, is computed as the Euclidean distance between their industry weight vectors:

$$\text{Distance}_{m,n,t} = \frac{1}{\sqrt{2}}\sqrt{\sum_{j=1}^{J}(w_{m,j,t} - w_{n,j,t,})^2}. \tag{4.1}$$

In order to transform the pairwise distances into a single interconnectedness measure for each lead arranger, they suggest to take a (potentially weighted) average of the distances of bank i with respect to all others. That is, a bank's interconnectedness equals

$$\text{Interconnectedness}_{i,t} = 100 \times \left(1 - \sum_{k \neq i} x_{k,t} \times \text{Distance}_{i,k,t}\right), \tag{4.2}$$

where $x_{k,t}$ is the weight given to bank k at time t. The measure is naturally bounded between 0 and 100, with a higher number suggesting higher systemic interconnectedness through the syndicated loan market. We employ a size-weighted measure, where $x_{k,t}$ is the ratio of the $t-1$ total assets of bank k to the sum of all assets of banks which have completed a deal in the prior twelve months. This measure has the advantage that commonality with large banks leads to greater systemic risk, while commonality with a small firm is of lesser importance. Finally, in some parts of the paper we will explicitly focus on, arguably, the largest systemic event; the collapse of Lehman Brothers on September 15th, 2008.[3] In those specific tests we will also use the firms' interconnectedness with Lehman:

$$\text{Interconnectedness}_{i,t}^{\text{Lehman}} = 100 \times (1 - \text{Distance}_{i,\text{Lehman},t}). \tag{4.3}$$

Note that this is a strictly backward-looking measure, i.e. it measures the interconnectedness based on the deals signed twelve months prior to Lehman's collapse.

Finally, we proxy the effect of signing a loan on interconnectedness by means of a measure we term ΔInterconnectedness. The ΔInterconnectedness measure is defined at the loan-facility level, by computing the percentage change in Interconnectedness, end-of-month after signing, relative to end-of-month pre-signing. This measure provides us with a directional news shock in terms of the interconnectedness of the bank.

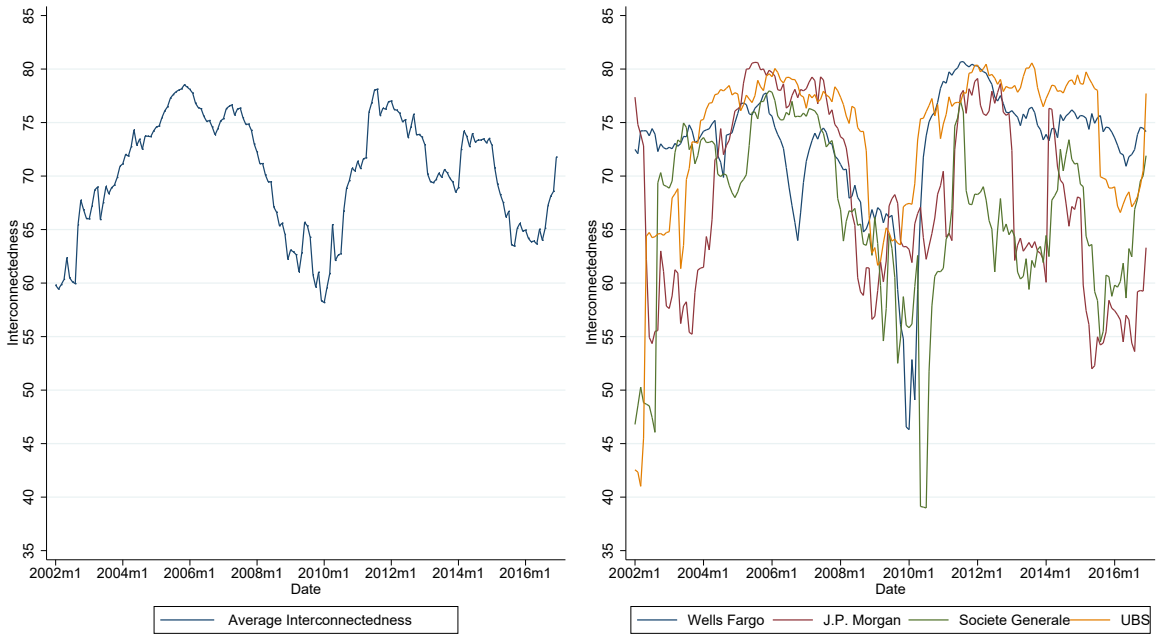
We summarize the interconnectedness measure by plotting its time-series characteristics in Figure 4.1. In the left-hand panel we plot the average interconnectedness across time, while on the right-hand side we provide a few examples for four specific banks. The interconnectedness had been steadily increasing up until 2008. Starting right around the collapse of Bear Stearns in March 2008 interconnectedness started to drop dramatically. The decline lasted more than two years. As the global economy started to strengthen, the average interconnectedness started to rapidly rise again. The final four years of our sample are characterized by slow decline with fewer dynamics.

Looking at the right-hand panel, we can clearly see the effect of the financial crisis

[3] Of course, the second half of 2008 contained many important systemic events. There is however little debate on the fact that the failure of Lehman was 'the first domino,' (see e.g. Brownlees and Engle (2016)).

Figure 4.1: Interconnectedness Dynamics

This figure plots the estimated interconnectedness based on Equation (4.2). The left panel plots the cross-sectional average interconnectedness measure across time, while the right-hand panel plots the interconnectedness of a number of international example firms.



on the various firms. The decline in interconnectedness of J.P. Morgan and UBS is far less pronounced than for the other two firms. In particular, Société Générale's interconnectedness drops by about 50% over a three year period, and takes until 2011 to recover, while UBS is at its old level in 2010. Société Générale also seems to be much harder hit by the European Debt crisis, in line with its base of operations.

4.3 Data and Descriptive Statistics

Data on banks and their syndicated loans are obtained from LPC DealScan. We obtain information on the bank, its role in the syndicate and the size of the loan. Since our focus is on banks of systemic importance, we remove all deals of banks with fewer than ten deals throughout our sample period of 1986 to 2016. In total we have almost 500,000 deals, spread out over 394 months and 959 different lead arrangers, who provided syndicated loans to a large number of firms spanning 84 two-digit SIC industries. We use this data to compute the interconnectedness measure described in the previous section for each lead-arranger month.

Stock market information for the banks in our sample are obtained from CRSP for US banks, and Datastream for non-US banks, for the period 1980 to 2016. We match stock market data to the above mentioned dataset by bank name. We obtain bank financial information from Compustat NA for US banks, and from Compustat Global for non-US

Table 4.1: Descriptive Statistics

This table provides the descriptive statistics for all variables of interest as well as control variables. All variables but ΔInterconnectedness are at the firm-month level, while the former is at the loan-facility level. Spread is the 5-year CDS quote for senior debt issues, winsorized at the upper 1%. Size is the natural logarithm of total assets winsorized at 1%. Leverage is computed as short plus long-term debt, divided by total assets. Credit rating is an ordinal variable based on S&P ratings, where 1 is AAA, ranging to 21 for C/D. Idiosyncratic volatility is computed as the variance of monthly CAPM residuals, where parameters are estimated over the past 36-60 months depending on availability. Bid-ask spread is the bid-ask spread divided by the mid quote. Market return is last month's CRSP value-weighted index return. The risk-free rate is the one-month treasury bill rate. The Term structure slope is 10-year minus 2-year interest rate obtained from the Federal Reserve's H15 reports.

	N	Mean	Min	Median	Max	SD
Interconnectedness	5,377	58.80	25.19	63.19	80.23	16.41
ΔInterconnectedness	77,389	-0.10	-29.16	-0.04	31.98	1.53
Spread	5,444	94.58	3.207	75.84	554.5	83.20
Size	3,816	13.36	11.89	13.41	14.72	0.767
Leverage	4,209	0.301	0.0443	0.237	0.850	0.174
Credit rating	3,428	5.601	1	6	20	2.191
Idiosyncratic Volatility	3,885	89.97	5.990	62.89	559.8	101.8
Bid-ask spread	5,476	0.134	0.0108	0.0946	1.444	0.105
Market return	5,485	0.00728	-0.185	0.0118	0.114	0.0427
Risk free interest rate	5,338	2.067	-1.195	1.761	6.875	1.704
Term structure slope	5,485	1.560	-0.140	1.680	2.830	0.838

banks. We match this data to DealScan and the corresponding bank names, through GVKEYs using the matching list of Chava and Roberts (2008).

We obtain data on CDS spreads, as well as their bid and ask prices for the global banks in our sample from Bloomberg for the period 2002 to 2016. We use monthly data on 5-year CDS quotes for senior debt issues, as these are generally regarded as the most liquid CDS available. Sufficiently liquid data on CDS prices is available for only a limited number of banks, resulting in a sample of 60 of the major banks. The dataset covers the most important financial institutions, and contains all, but two Chinese banks on the 2017 list of G-SIBs, published by the financial stability board (FSB, 2017). The CDS spreads are matched to DealScan based on bank name.

Descriptives of the resulting variables are provided in Table 4.1. It bears noting that all variables, except for ΔInterconnectedness, are at the firm-month level. ΔInterconnectedness is at the loan-facility level. All the remaining variables are used in our CDS analysis along with the Interconnectedness variable. The ΔInterconnectedness variable is used in our event study, in conjunction with standard daily CRSP data.

4.4 Syndication Interconnectedness and the Equity Market

In this section we investigate whether or not equity markets react to changes in the composition of the loan portfolio of the major financial institutions. Our analysis consists of two parts. First, we consider one of the biggest shocks to the financial system of the last decades, the fall of Lehman Brothers on September 15th, 2008. We investigate the stock market reaction of the other financial institutions to its demise. In this case, we are primarily interested in whether or not investor reaction to financial firms that were more tightly linked to Lehman, through the syndicated loan market, was stronger. Second, we investigate whether the equity market generally reacts to news regarding the network of syndicated lending. To that effect, we look at the stock market reactions to the announcement of each of the loans in the DealScan sample. One would not necessarily expect a market reaction to the mere signing of a deal on the banks' side. While obtaining a large loan can have a strong positive impact on the borrower (e.g. Gasbarro, Le, Schwebach, and Zumwalt, 2004), it could also be regarded as daily business of the leadarrangers. Stock markets may, however, react if the signing of the loan has a strong impact on the risk of the financial institution.

For each event, we collect equity market (simple) returns around the completion date. We measure return performance by cumulating daily abnormal returns around the deal completion. We consider the pre-event date $[-1, -1]$, the event date itself $[0, 0]$, as well as post-event windows $[1, 1]$, $[1, 3]$ and $[1, 5]$. We compute daily abnormal returns based on the methodologies described in Brown and Warner (1985). In particular, we compute the abnormal returns relative to the three-factor model of Fama and French (1993), where the factor loadings are obtained using OLS estimates in a 'clean' period of 252 to 21 days before the event where available, with a minimum number of 120 observations. The market, HML and SMB factors are obtained from Kenneth French's website.

Since our hypothesis is that the market's reaction should depend on the interconnectedness, we consider a linear regression on the cumulative abnormal returns. We adjust the standard errors for heteroskedasticity using White's (1980) robust covariance matrix. While the events in the second part of our analysis are randomly spread across time, there may be some concerns of event-induced variance for the Lehman analysis. (e.g. Boehmer, Masumeci, and Poulsen, 1991). In their nomenclature, our implementation may best be compared to the 'Ordinary cross-sectional' tests, augmented to allow for cross-sectional heteroskedasticity. Compared to their suggested 'Standardized cross-sectional' implementation, their simulations show the Ordinary version controls size slightly better at the cost of lower power, which we prefer.

4.4.1 Equity Market reactions to Lehman's Failure

We start our analysis of the stock market around the collapse of Lehman. For each firm, we compute the $\text{Interconnectedness}_{i,t}^{\text{Lehman}}$ measure of Equation (4.3) in August 2008, as well as the CARs around the event date of September 15, 2008. Our sample consists of a total of 43 firms for which we have sufficient data to compute both the interconnectedness measure and the CARs.

The resulting regression estimates are presented in Table 4.2. First consider Panel A, which is based on the raw returns. Specification I shows that the failure of Lehman had a large effect on the firms in our sample, with a negative return of 9% on the [0,0] window, but the stock prices bounced back by nearly 12% over the next five days. Specification II shows that this rebound was weaker for those firms that were tightly linked to Lehman through the syndicated loan market. The cross-sectional standard deviation of interconnectedness of these firms was about 38, such that a one standard-deviation increase in interconnectedness would decrease the [1,5]-CAR by almost 5%. Specification III shows that this was not just a geographical proximity effect, as $\text{IC}^{\text{Lehman}}$ remains significant after including country fixed effects.[4]

Panel B, which reports the same regressions for abnormal returns based on the Fama-French three factor model confirms the result of the raw returns. Interestingly, specification I shows that the financial firms were not hit harder than their usual risk exposures would suggest, but their rebound was in fact stronger. The second specification confirms the sign and magnitude of the effect of the interconnectedness with Lehman on the stock market reaction to its failure, and is near identical to the results based on raw returns.

4.4.2 Equity Market Reactions to Syndicated Loans

The results of Table 4.2 establish that firms more closely related to Lehman in the syndicated loan market were affected more strongly by Lehman's failure. These results are perhaps not entirely surprising. It has been well established that stock markets react to news, and stock prices of firms that are directly and strongly affected by said news, react more strongly. The interconnectedness measure captures how close the bank's business is to that of Lehman. As a result, the interpretation may be two-fold; either it is simply the proximity to Lehman - after all, these are all large financial institutions - or, investors actually react to the risk inherent in the interconnectedness.

To differentiate these two potential explanations we try to establish whether markets react explicitly to changes in the interconnectedness of the syndicated loan market. We therefore use the standard event-study approach to measure the market reaction to syndicated loan announcements. We are particularly interested in the extent to which abnormal equity returns are a function of the impact of the loan signed on the syndication-driven

[4]More generally, all the results in the remainder of this chapter are robust to the inclusion of country fixed effects, but have not been reported for the sake of brevity. The results are available upon request.

Table 4.2: Equity Market Reaction to Syndicated Loans: Lehman's Failure

This table investigates the market reaction on banks' equity around Lehman's failure on September 15, 2008, as a function of the interconnectedness the banks had with Lehman. The table provides OLS estimates, with White (1980) robust standard errors, of a constant and Lehman Interconnectedness, Equation (4.3), on Cumulative Abnormal Returns. Each column corresponds to a different CAR window. The top panel computes CARs based on raw returns, while the bottom panel uses Fama-French three-factor abnormal returns. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

CAR		[-1,-1]	[0,0]	[1,1]	[1,3]	[1,5]
Panel A: Raw Returns						
I	Constant	-0.228	-8.908***	4.653***	7.092***	11.78***
		(0.480)	(0.828)	(1.197)	(2.217)	(2.442)
II	IC^{Lehman}	-0.00275	-0.0146	-0.0604***	-0.131**	-0.125***
		(0.0142)	(0.0114)	(0.0215)	(0.0491)	(0.0382)
	Constant	-0.0674	-8.055***	8.173***	14.75***	19.04***
		(1.069)	(1.189)	(2.160)	(4.217)	(4.301)
III	IC^{Lehman}	-0.00186	-0.0191*	-0.0690**	-0.143**	-0.129**
		(0.0139)	(0.0111)	(0.0278)	(0.0656)	(0.0525)
	Country FE	Yes	Yes	Yes	Yes	Yes
Panel B: Fama-French Three Factor Abnormal Returns						
I	Constant	-0.492	0.364	0.00920	0.957	5.478**
		(0.502)	(0.840)	(1.159)	(2.023)	(2.318)
II	IC^{Lehman}	-0.00308	-0.0166	-0.0606**	-0.124**	-0.120***
		(0.0138)	(0.0109)	(0.0228)	(0.0490)	(0.0367)
	Constant	-0.314	1.325	3.524	8.145**	12.46***
		(1.061)	(1.273)	(2.148)	(4.005)	(4.152)
III	IC^{Lehman}	-0.00205	-0.0206	-0.0681**	-0.133**	-0.122**
		(0.0142)	(0.0122)	(0.0262)	(0.0537)	(0.0470)
	Country FE	Yes	Yes	Yes	Yes	Yes

interconnectedness of the lenders. The loan announcement is news to the market, and the resulting changes in interconnectedness proxy the severity and sign of the shock. To achieve this, for each signed loan, we compute the percentage change in interconnectedness of next month, with respect to the current level of interconnectedness, which we refer to as Δ Interconnectedness.

We obtain a total of nearly 78,000 loan announcements from DealScan for which we can compute the ΔInterconnectedness measure and CARs. A loan signing occurs almost every single day, which raises the concern of clean identification of an effect. This issue is mitigated by two factors. First, since events happen on almost every day, the raw return would simply be a proxy for the average return over the entire sample, and is therefore not informative. The Fama-French residual returns do not suffer from this problem. Second, if the ΔInterconnectedness measure is significant, a spurious results would entail that some other event systematically happens to those banks that signed a loan, in the short

Table 4.3: Equity Market Reaction to Syndicated Loans: General Interconnectedness - Linear Specifications

This table investigates the market reaction on banks' equity to changes in the interconnectedness of their loan-portfolio over the period 1986 to 2016. The table provides OLS estimates, with White (1980) robust standard errors for regressions on Cumulative Abnormal Returns. Each column corresponds to a different CAR window. ΔIC is defined as the percentage change in monthly interconnectedness after the signing of the announced deal. Post-Lehman is a dummy which equals one for after September 15, 2008. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

CAR		[-1,-1]	[0,0]	[1,1]	[1,3]	[1,5]
I	Constant	0.00218	0.00866	0.0202***	-0.00563	0.0300*
		(0.00751)	(0.00747)	(0.00751)	(0.0130)	(0.0164)
	ΔIC	-0.00809	-0.0204*	-0.0487***	-0.0825***	-0.179***
		(0.0114)	(0.0121)	(0.0115)	(0.0198)	(0.0253)
II	Constant	0.00218	0.00866	0.0202***	-0.00563	0.0300*
		(0.00751)	(0.00747)	(0.00751)	(0.0130)	(0.0164)
	ΔIC	-0.00450	0.0169	-0.0319**	-0.0158	-0.103***
		(0.0137)	(0.0150)	(0.0140)	(0.0241)	(0.0304)
	ΔIC	-0.0104	-0.108***	-0.0484***	-0.193***	-0.221***
	× Post Lehman	(0.0164)	(0.0180)	(0.0168)	(0.0286)	(0.0372)
III	Constant	0.00791	0.0118	0.0197*	0.000330	0.0436*
		(0.0103)	(0.0103)	(0.0103)	(0.0177)	(0.0223)
	Post Lehman	-0.0152	-0.00840	0.00132	-0.0158	-0.0362
		(0.0146)	(0.0145)	(0.0147)	(0.0253)	(0.0321)
	ΔIC	-0.0102	0.0137	-0.0314**	-0.0217	-0.116***
		(0.0154)	(0.0165)	(0.0156)	(0.0269)	(0.0340)
	ΔIC	0.00485	-0.0992***	-0.0497**	-0.177***	-0.185***
	× Post Lehman	(0.0219)	(0.0231)	(0.0223)	(0.0382)	(0.0491)

period following the exact announcement date, which is correlated with the impact that loan has on the interconnectedness of the firm's loan portfolio. It seems unlikely that such a pattern would exist by sheer chance.

We present the results of our analysis in Table 4.3. As stated before, we only consider the Fama-French adjusted returns, to control for most market wide events. Specification I considers a constant and ΔInterconnectedness. Importantly, there appears to be no pre-announcement effect at all. On the day of the announcement, there appears to be no systematic average return effect, but we do observe a marginally significant coefficient on ΔInterconnectedness. Indeed, if a loan increases the interconnectedness of the financial institution, there is a small, but statistically significant negative effect on its share price. Rather, the effect appears to move slower and accumulate over time. Indeed, looking at the [1,5] CAR, we observe a statistically convincing, moderately large negative effect of ΔInterconnectedness.

Specifications II and III further investigate how the equity market reacted to increasing interconnectedness in light of the Lehman event, which highlighted the fragility of the financial system. Indeed, specification II suggests that the announcement date effect

Table 4.4: Equity Market Reaction to Syndicated Loans: General Interconnectedness - Piecewise Constant Specification

This table investigates the market reaction on banks' equity to changes in the interconnectedness of their loan-portfolio over the period 1986 to 2016. The table provides OLS estimates, with White (1980) robust standard errors for regressions on Cumulative Abnormal Returns. Each column corresponds to a different CAR window. ΔIC α% is a dummy variable which equals one if the ΔIC associated with the deal exceeds the α% quantile. Robust standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

CAR		[-1,-1]	[0,0]	[1,1]	[1,3]	[1,5]
I	Constant	-0.00147	-0.000777	-0.00255	-0.0449***	-0.0542***
		(0.00567)	(0.00600)	(0.00575)	(0.00990)	(0.0126)
	ΔIC 1%	-0.0330	-0.0387	0.0784	0.0534	0.193
		(0.0822)	(0.0814)	(0.0754)	(0.123)	(0.158)
	ΔIC 99%	0.0424	0.0382	-0.103*	-0.153	-0.309**
		(0.0609)	(0.0623)	(0.0609)	(0.102)	(0.137)
II	Constant	-0.00231	0.00108	-0.0116*	-0.0498***	-0.0596***
		(0.00583)	(0.00620)	(0.00591)	(0.0102)	(0.0129)
	ΔIC 5%	-0.0127	0.0189	-0.0570*	-0.0558	0.0322
		(0.0322)	(0.0305)	(0.0313)	(0.0529)	(0.0676)
	ΔIC 95%	-0.00218	0.0181	-0.128***	-0.0635	-0.165**
		(0.0277)	(0.0306)	(0.0293)	(0.0492)	(0.0667)
III	Constant	-0.00290	0.00573	-0.00720	-0.0438***	-0.0402***
		(0.00623)	(0.00660)	(0.00631)	(0.0109)	(0.0138)
	ΔIC 10%	-0.0331	0.0270	-0.0143	-0.00675	0.0745*
		(0.0202)	(0.0202)	(0.0199)	(0.0345)	(0.0440)
	ΔIC 90%	0.0197	0.0379*	-0.0346*	0.00694	0.0532
		(0.0194)	(0.0210)	(0.0201)	(0.0338)	(0.0445)

only started after Lehman. The magnitude of the coefficient is five times as large as the equivalent coefficient in specification I. The cumulative effect, as captured by the longer horizon CARs, also demonstrates that markets reacted much more heavily to similarly sized shocks following this first systemic event. Finally, specification III confirms that this is not merely a mean-effect in the returns post-Lehman.

To investigate the economic magnitude of the coefficients, consider a median loan signing. The median loan actually decreases the interconnectedness of a firm by -0.04%. For such a loan, based on specification III, the expected announcement return is a mere 0.004%. In short, such a loan has no impact on the stock price, which is to be expected. Signing syndicated loans is part of the daily business of financial institutions, and as long as nothing changes to the risk of the bank, its valuation should not fundamentally change.

Alternatively, we can consider a higher quantile of the distribution of ΔInterconnectedness. Its 95% quantile equals 1.44, resulting in an abnormal announcement return of -0.143%, which is still moderately small. However, the 5-day CAR accumulates to 0.432%. In fact, the predicted 5-day CAR exceeds negative 1% for about 1.2% of the deals signed.

The magnitude of the coefficients suggest that the stock market reaction is to the tails of the distribution; stock market reactions only occur for signed loans which have

a large negative impact on the interconnectedness of the lead arrangers. To test this more formally, we construct $\Delta\text{Interconnectedness}_\alpha$ dummies, which equal 1 if the variable exceeds its α quantile in the natural direction, and zero otherwise. Table 4.4 considers such piecewise constant specifications, using both left- and right-hand side quantiles of ΔInterconnectedness. Specifications I, II and III consider the 1, 5 and 10%, respectively, of deals that had the largest impact on Interconnectedness in either direction.

The table shows that indeed, the signing of a loan only has a stock market reaction if the loan is severely detrimental to the interconnectedness of the firm. Looking at specification I, we observe a -0.31% return for the 1% most increasing loans, and no stock market reaction to the bottom extremes. The magnitude of the coefficient becomes smaller when we consider the 5% most increasing deals, and becomes insignificant when we consider the 10% most detrimental deals in Specification III.

Overall, we conclude that the equity market does appear to react to interconnectedness stemming from syndicated loans, but only if the loan has a severely detrimental effect on the bank's interconnectedness. For most of the loans, there is no significant stock reaction. This is not unexpected given that the signing of syndicated loans is business as usual, there is no real news.

4.5 Syndication Interconnectedness and the CDS Market

The previous section showed that the equity market is mostly concerned with the severe downside of interconnectedness. Correspondingly, an investigation of the market reactions to the risk stemming from syndicated loans is ideally suited to the CDS market, which by construction only looks at the extreme down-side risk of companies.

In this section, we therefore consider to what extent the level of interconnectedness is priced in CDS spreads for the major financial banks. Our empirical approach is based on the following fixed-effects panel specification:

$$\text{CDS}_{i,t} = \beta_1 \text{Interconnectedness}_{i,t} + \boldsymbol{\beta}_2' \mathbf{X}_{i,t}^{Firm} + \boldsymbol{\beta}_3' \mathbf{X}_t^{Market} + \boldsymbol{\beta}_4' \mathbf{X}_{i,t}^{CDS} + \gamma_i + \delta_t + \epsilon_{i,t} \quad (4.4)$$

where $\text{CDS}_{i,t}$ is bank i's spread in month t, $\text{Interconnectedness}_{i,t}$ is the interconnectedness of bank i at time t to other banks in the system. $\mathbf{X}_{i,t}^{Firm}$ is a vector of bank specific information, $\mathbf{X}_t^{Market}$ is a vector of market wide and macro economic variables, and $\mathbf{X}_{i,t}^{CDS}$ is a vector of CDS specific control variables. We use 5 year CDS quotes for senior debt issues at the monthly interval, since these are generally considered to be the most liquid. We organize our specifications and results discussion in three groups, bank specific factors, market wide factors, and CDS specific factors. While contemporaneous, all variables on the right-hand side are observable at the time the CDS spread is measured, which is the end of the month.

We follow previous literature on CDS pricing in controlling for factors known to affect movements in CDS prices. We control for bank specific factors, market factors and CDS microstructure factors shown to influence CDS prices. We start by controlling for bank size, leverage and credit rating following Drago, Di Tommaso, and Thornton (2017) Benkert (2004) and Ericsson, Jacobs, and Oviedo (2009). Leverage is expected to be positively related to spreads, as it increases bank default risk. Larger banks are expected to be better able to weather difficult times, therefore, we expect size to be negatively related to spreads. We obtain data on leverage and the log of total assets (size), from Compustat NA and Compustat Global. Credit ratings are strongly related to the default probability of the bank. We transform credit ratings into discrete numbers where the AAA-rating takes on the lowest value and the D-rating takes on the highest value. As a result, we expect credit ratings to be positively related to spreads. The riskier the bank, the higher the numerical rating, the higher the spread. S&P credit ratings are obtained from Compustat and Bloomberg for all banks in our sample. Lastly, we control for bank idiosyncratic risk following Ericsson, Jacobs, and Oviedo (2009) and Annaert, De Ceuster, Van Roy, and Vespro (2013). We compute the idiosyncratic variance as the variance of CAPM residuals, estimated over the past five years of monthly stock return data, obtained from CRSP. Theoretically, higher volatility leads to higher default risk, which is, in turn, positively related to CDS spreads.

We control for market wide factors, because general macro economic conditions have a significant effect on probabilities of default. We follow Annaert, De Ceuster, Van Roy, and Vespro (2013), Drago, Di Tommaso, and Thornton (2017), Alexander and Kaeck (2008), Collin-Dufresne and Goldstein (2001), Ericsson, Jacobs, and Oviedo (2009), and Duffie, Saita, and Wang (2007) by including the contemporaneous monthly CRSP value-weighted return as a control variable. Improvements to general economic conditions are likely to decrease probabilities of default and increase recovery rates (Annaert, De Ceuster, Van Roy, and Vespro, 2013). We also include a measure for market wide volatility to proxy for the business climate following Benkert (2004), Drago, Di Tommaso, and Thornton (2017), and Annaert, De Ceuster, Van Roy, and Vespro (2013). The assumption here is that a higher level of volatility is associated with with higher levels of uncertainty about economic prospects. It follows that we expect market volatility to have a positive relationship with spreads. We measure market wide volatility as the variance of the past five years of monthly CRSP's value-weighted return. We control for the risk free interest rate based on Merton (1974), where the risk-free rate represents the drift in the risk neutral world, where the higher the rate, the smaller the probability of default (Annaert, De Ceuster, Van Roy, and Vespro, 2013; Benkert, 2004; Drago, Di Tommaso, and Thornton, 2017; Ericsson, Jacobs, and Oviedo, 2009; Fabozzi, Cheng, and Chen, 2007). It follows that we expect to find a negative relationship between spreads and the risk free interest rate. Another possible explanation for the expected relationship is that higher risk free rates signal economic growth, and as a result, default becomes less

probable. Lastly, we include a measure for the slope of the term structure, which is widely seen as a predictor of the business cycle (see e.g. Estrella and Mishkin, 1997). We expect a negative relationship between the slope of the term structure and spreads, because a high slope indicates expected economic growth. Similarly, a negative relationship may stem from a high slope, to the extent that it carries information about future interest rate levels, which implies lower credit risk (Annaert, De Ceuster, Van Roy, and Vespro, 2013). Following Annaert, De Ceuster, Van Roy, and Vespro (2013), we take the difference between the 10 year and the 2 year yields as reported by the Federal Reserve's H.15 forms. Despite having a global sample, our macro-economic controls are all US-based. For a large number of countries some of the control variables are simply not available. Given the monthly frequency of our analysis, the US-based measures will typically capture the worldwide slow-moving patterns in variables, decreasing the significance of the limitation.

Finally, we control for CDS specific information. We follow Annaert, De Ceuster, Van Roy, and Vespro (2013) and Fabozzi, Cheng, and Chen (2007) and control for the bid-ask spread. Bongaerts, De Jong, and Driessen (2011) develop a theoretical asset pricing model, which predicts that derivative securities may also contain liquidity premia. They confirm empirically that part of the CDS spread is indeed due to liquidity. Similarly, Fabozzi, Cheng, and Chen (2007) also find that liquidity has a significant effect on CDS spreads. We measure liquidity as the relative bid-ask spread on CDS quotes, (bid-ask)/midquote, following Annaert, De Ceuster, Van Roy, and Vespro (2013). Based on findings by the above mentioned papers, we expect to find a negative relationship between interest rates and spread.

4.5.1 CDS Market Reactions to Lehman's Failure

Previous research shows that banks that are interconnected, and those that are more similar to failing institutions, generally suffer more when the respective institution fails (Dumontaux and Pop, 2013; Ivashina and Scharfstein, 2010a). We start by investigating whether banks that are interconnected to Lehman, experience greater negative effects on the market. Specifically, we look at whether surviving institutions interconnected to Lehman through syndicated loans experience higher spreads in the CDS market.

Table 4.5 shows our panel specification of Equation (4.4), where we use the IC^{Lehman} measure of Equation 4.3, rather than the general interconnectedness, and our sample is naturally restricted to those banks and time-periods that had business dealings with Lehman. We consider five different specifications. All specifications have bank and year fixed effects, and use standard errors clustered by bank and year. The first specification merely estimates the impact of the level of interconnectedness with Lehman on the CDS spreads.

As all regressions show, the more interconnected to Lehman the surviving banks are, the higher their CDS spreads become, which in turn means, the more likely to default they are according to investors. The average Interconnectedness with Lehman is about 60 with

Table 4.5: CDS Market Reaction to Syndicated Loans: Lehman's Failure

This table investigates the pricing of banks' CDS spreads around Lehman's failure on September 15, 2008, as a function of the interconnectedness the banks had with Lehman. This table presents OLS estimates with standard errors clustered by firm and year. IC^{Lehman} is the firms' interconnectedness with Lehman, computed as in Equation (4.3). Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
IC^{Lehman}	0.876***	2.413***	0.794***	0.901***	2.595***
	(0.288)	(0.502)	(0.274)	(0.289)	(0.555)
Size		-78.32***			-74.71***
		(13.93)			(15.09)
Leverage		6.706***			6.533***
		(1.320)			(1.304)
Ratings		21.06***			23.15***
		(6.074)			(5.500)
Idiosyncratic volatility		0.921***			0.626***
		(0.238)			(0.214)
Risk-free interest rate			-17.55***		-25.96***
			(2.546)		(7.078)
Term structure slope			-5.932		-17.81
			(7.787)		(12.72)
Market Return			-1.700**		-2.319***
			(0.678)		(0.736)
Market Volatility			1.851		-0.212
			(1.329)		(1.817)
Bid-Ask spread				-97.45***	-8.375
				(31.72)	(63.40)
Observations	538	263	538	538	263
Adjusted R-squared	0.742	0.839	0.766	0.745	0.854
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes

a standard deviation of 20. Hence, a one-standard deviation increase in interconnectedness increases the CDS spread by about 17.5bp, which is both statistically and economically significant, given that the average spread over the this sample is around 110 bps. The next three specifications control for bank, market, and CDS specific variables respectively. All variables, but the Bid-Ask spread, have the expected sign and natural magnitudes. The unexpected effect of the Bid-Ask spread can be explained by the discreteness of CDS spreads in the early sample. CDS spreads were mostly quoted up to one-eights of dollars up until 2006. As a result, the relative bid-ask spread is inherently higher for low-spread observations where relatively large relative bid-ask spreads may occur for cheap contracts. Regression (5) considers the interconnectedness measure and all controls. The impact of interconnectedness increases roughly three-fold compared to the simple regression, suggesting that during this time-period, a one standard deviation increase in interconnectedness with Lehman, increased CDS spreads by over 50bps, which is large

Table 4.6: CDS Market Reaction to Syndicated Loans: General Interconnectedness I

This table investigates the market pricing of on banks' CDS spreads to the level of interconnectedness of their loan-portfolio over the period 2002 to 2016. This table presents OLS estimates with standard errors clustered by firm and year. IC is the firms' interconnectedness measure, computed as in Equation (4.2). Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
IC	0.133*	0.159	0.0935	0.126*	0.198
	(0.0754)	(0.135)	(0.0745)	(0.0750)	(0.126)
Size		-17.41***			-27.16***
		(5.545)			(5.589)
Leverage		1.383***			1.444***
		(0.314)			(0.299)
Ratings		2.856*			3.150**
		(1.565)			(1.469)
Idiosyncratic volatility		0.0867*			0.0341
		(0.0523)			(0.0503)
Risk-free interest rate			-4.875***		-1.824
			(1.213)		(1.887)
Term structure slope			-26.99***		-33.80***
			(3.186)		(4.741)
Market Return			-2.127***		-2.107***
			(0.248)		(0.336)
Market Volatility			2.726***		2.432***
			(0.416)		(0.553)
Bid-Ask spread				-83.15***	-139.8***
				(9.907)	(19.10)
Observations	5,336	2,269	5,208	5,328	2,224
Adjusted R-squared	0.634	0.641	0.653	0.639	0.671
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes

considering the fact that the unconditional standard deviation of CDS spreads is around 110 in this sub-sample.

The results in Table 4.5 show that large shocks are indeed observed by the market and investors react. However, the more interesting question is whether investors only react to large shocks, or whether they also react to smaller movements in the market. We consider the full sample, and the general Interconnectedness measure of Equation (4.3) in Table 4.6. The table follows the same general format as Table 4.5. The coefficients on the control variables typically have the same sign and magnitude as in the previous specification. The coefficients on interconnectedness however have strongly decreased, and mostly become insignificant. The table suggests that over the 2002-2016 period, loan-syndicate members interconnectedness was not priced in CDS spreads.

In order to reconcile the apparent inconsistency between the two tables, we investigate the impact of Lehman's failure on the relationship between interconnectedness and CDS

Table 4.7: CDS Market Reaction to Syndicated Loans: General Interconnectedness II

This table investigates the market pricing of on banks' CDS spreads to the level of interconnectedness of their loan-portfolio over the period 2002 to 2016. This table presents OLS estimates with standard errors clustered by firm and year. IC is the firms' interconnectedness measure, computed as in Equation (4.2). Post Lehman is a dummy variable taking the value of one starting October 2008. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
IC	-0.179*	-0.228	-0.159*	-0.199**	-0.196
	(0.0926)	(0.166)	(0.0918)	(0.0924)	(0.160)
IC × Post Lehman	0.515***	0.654***	0.403***	0.536***	0.646***
	(0.107)	(0.171)	(0.102)	(0.107)	(0.174)
Size		-18.73***			-29.72***
		(5.524)			(5.659)
Leverage		1.635***			1.715***
		(0.319)			(0.304)
Ratings		2.069			2.648*
		(1.588)			(1.481)
Idiosyncratic volatility		0.0747			0.0451
		(0.0517)			(0.0499)
Risk-free interest rate			-4.748***		-0.290
			(1.203)		(1.839)
Term structure slope			-29.24***		-37.80***
			(3.113)		(4.628)
Market Return			-2.006***		-1.922***
			(0.244)		(0.332)
Market Volatility			2.149***		1.536***
			(0.384)		(0.506)
Bid-Ask spread				-85.43***	-141.4***
				(9.924)	(19.00)
Observations	5,336	2,269	5,208	5,328	2,224
Adjusted R-squared	0.638	0.646	0.655	0.643	0.675
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes

spreads. Table 4.7 includes an interaction term between interconnectedness and a post-Lehman Brothers bankruptcy dummy. The issue of systemic risk became well-known and much more pressing following its first realization in recent memory. While the inherent risk due to the interconnectedness did not necessarily increase after Lehman, it did partly realize, which potentially lead to simple awareness of the risk. Indeed, the fact that markets quickly adapt prizes to newly discovered patterns is not new (e.g. McLean and Pontiff, 2016).

All specifications are the same as those presented in Table 4.6, except we include the interaction term in all of them. Across specifications, the pre-Lehman Interconnectedness coefficient is small or statistically zero, while the post-Lehman coefficient is economically

Table 4.8: CDS Market Reaction to Syndicated Loans: General Interconnectedness III

his table investigates the market pricing of on banks' CDS spreads to the level of interconnectedness of their loan-portfolio over the period 2002 to 2016. This table presents OLS estimates with standard errors clustered by firm and year. IC is the firms' interconnectedness measure, computes as in Equation (4.2). Post Bear Stearns is a dummy variable taking the value of one starting April 2008, while Post EU crisis takes the value one starting June 2010. Clustered standard errors in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
IC	0.0486	0.0310	0.0652	0.262*
	(0.0781)	(0.136)	(0.0827)	(0.143)
IC × Post Bear Stearns	0.131*	0.268**		
	(0.0755)	(0.136)		
IC × Post EU crisis			0.125**	-0.107
			(0.0583)	(0.0877)
Size		-28.02***		-26.86***
		(5.654)		(5.592)
Leverage		1.541***		1.411***
		(0.307)		(0.294)
Ratings		2.835*		3.155**
		(1.473)		(1.467)
Idiosyncratic volatility		0.0310		0.0348
		(0.0505)		(0.0504)
Risk-free interest rate		-1.891		-1.967
		(1.906)		(1.893)
Term structure slope		-33.97***		-34.29***
		(4.703)		(4.808)
Market Return		-2.099***		-2.086***
		(0.335)		(0.338)
Market Volatility		2.325***		2.483***
		(0.544)		(0.561)
Bid-Ask spread		-140.2***		-140.3***
		(19.12)		(19.16)
Observations	5,336	2,224	5,336	2,224
Adjusted R-squared	0.635	0.671	0.635	0.671
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes

and statistically large. The coefficient on the interaction term is significant and positive in all specifications and ranges from 0.5 to 0.65. Taking the full specification (5) to illustrate the economic magnitude of interconnectedness, we see that a one standard deviation, about 17bps in the full sample, increase in interconnectedness leads to a 11bp increase in spreads. This effect may seem small, but represents approximately 10% of the average spread in our sample.

It appears that the post Lehman CDS spreads more accurately reflect the systemic risk of the financial system, as proxied by the syndicated loan interconnectedness measure.

Two remarks are in order. Despite the fact that Cai, Eidam, Saunders, and Steffen (2018) show that the syndication based interconnectedness measure is distinct from the more well known systemic risk meaures such as SRISK and ΔCovar, they are correlated, and the results of Table 4.7 should therefore be interpreted more broadly in the sense that CDS markets appear to price systemic risk since Lehman's fall.

Second, the results of the regression would look similar if a different event, which occurred within a reasonable time-frame, would cause the CDS market to start paying attention to systemic interconnectedness. We therefore consider two alternative critical economic events, which may drive the difference in pre- and post-Lehman effect of interconnectedness on spreads. Although Lehman Brothers was the most prominent event linked to the start of the financial system troubles, Brownlees and Engle (2016) point out that that the acquisition of Bear Stearns in March of 2008 and the European crisis of May 2010 were also seemingly important events. Table 4.8 presents results of the usual regressions (1) and (5), but includes interaction terms between interconnectedness and a dummy variable for each of these events, rather than the Lehman event. The magnitude of the coefficients for the Bear Stearns interaction is much smaller than that of Lehman, whilst the European crisis had no impact at all, confirming that Lehman appeared to be the event that sufficiently shook the market for them to incorporate the degree of interconnectedness in the spreads.

4.6 Conclusion

We investigate to what extent financial markets price the risk inherent in (systemic) interconnectedness. We measure the interconnectedness of financial firms through their joint exposures to syndicated loans, using a dataset of nearly half a million deals. Our analysis considers both the equity market and the downside-focused Credit Default Swaps market. The results are mostly consistent; both markets adapted their behavior to the new reality of large financial firms failing following the demise of Lehman Brothers.

We confirm prior research by documenting that both markets reacted heavily to the failure of Lehman itself. Moreover, firms that were tightly connected to Lehman had stronger negative stock price reactions, and their CDS spreads were generally higher. The fact that markets reacted to this big news is indeed not too surprising. In this paper we dig deeper into the systemic risk inherent in the syndicated loan market, and investigate to what extent small changes, or differences, in interconnectedness spurred reactions in financial markets. We find that the level and shocks to interconnectedness mostly occurred without impact pre-Lehman, but garner strong market reactions post-Lehman, and continue to do so.

In terms of the equity market, we find that markets react strongly to the announcement of deals that have a large negative impact on the degree of interconnectedness. The economic and statistical significance of the result is driven by 5% of deals that led to the

largest increase in interconnectedness. There is no such impact in the middle or the left-tail of the distribution, suggesting that most syndicated loans are treated as day-to-day business, and that equity markets mainly care about the potential downside risk of such deals.

CDS prices did not reflect the inherent risk of interconnectedness pre-Lehman. Controlling for a large set of firm and market characteristics, we find that post-Lehman, CDS spreads are strongly related to the level of interconnectedness of the firm. Similar to the equity results, the CDS market now recognizes and prices the inherent downside risk of interconnectedness.

Our results show that market participants recognize, and are worried about, the systemic interconnectedness in the syndicated loan market. After the risk materialized during the financial crisis, banks paused their systemic risk increasing behavior briefly, but quickly resumed business as usual soon after the shock. Market participants however, are clearly still worried about the potential negative effects of this strong network.

Indeed, our findings suggest that perhaps the financial system may actually be more stable if banks were to diversify their risks less. This point has been made earlier by De Vries (2005), who argues that risk concentration may lead to more frequent individual bank failures, but that the risk segregation will likely reduce the risk of a systemic breakdown.

A natural objective of regulation is to increase the stability and resilience of the financial system by regulating the extent and nature of interbank linkages. This paper, in line with Cai, Eidam, Saunders, and Steffen (2018), provides evidence to suggest that linkages through large corporate loans should also be taken into account in measuring interconnectedness, and potentially be limited by regulations. The current assessment methodology for Global Systemically Important Banks involves indicators regarding five broad categories; size, interconnectedness, lack of readily available substitutes or financial institution infrastructure, global (cross-jurisdictional) activity, and complexity (BIS, 2013). Although interconnectedness is taken into account, the measure is based on direct exposure among financial institutions. Our results show that indirect linkages appear to be a point of concern for financial markets as well, and should be explicitly taken into account.

Importantly, the paper shows that market participants appear to be actively monitoring the interconnectedness stemming from syndicated loan markets. Interconnectedness increasing moves by banks are punished through higher costs of capital. This demonstrates how the market plays an active role in the monitoring of systemic risk of large financial institutions, above and beyond the limitations imposed by regulating agencies.

Overall, the paper shows that the old adage of mere upside of syndication is over, and market participants are concerned about the underexposed negative implications of syndication. Risk is not appropriately diversified if it is spread across a small group of highly influential and large financial institutions, and this is recognized by the market.

Chapter 5

Conclusion

Syndicated loan issuance has grown dramatically in the past years and it plays an increasingly important role in financing. It has become the dominant source of financing for corporations, outgrowing bond and equity issuance. Its size, in turn, makes it an important contributor to the financial system.

Broadly, this dissertation investigates syndicated loans from the perspective of borrowers and of the issuing banks. The first question this dissertation tries to answer is whether banks are social institutions, even in instances when the public is less aware of their dealings. We investigate this by looking at sin firms - firms in the alcohol, tobacco and gaming industry - and the spreads banks demand on their loans. Previous research found that sin firms experience a premium in equity markets. Investors shun these firms due to social constraints, which in turn affects their returns. We seek to investigate whether, in the reduced presence of public scrutiny, sin firms would experience similar outcomes.

In chapter 2, we find that sin firms consistently pay a lower spread on their loans, relative to otherwise similar firms. In an attempt to explain these results, we control for various aspects which have been shown to affect sin firms and/or loan conditions. We start by controlling for earnings quality, following Kim, Park, and Wier (2012). Our results show that although a better earnings quality does indeed have a negative relationship with loan spreads, it does not explain the lower spreads sin firms pay. We also control for bank-borrower relationship. When the bank is familiar with the borrower, spreads are on average lower, however, this does not explain the sin effect. Third, we control for firm beta. We follow the premise that when firms are anti-cyclical, they might be seen as a hedge opportunity by banks. We find that beta is positively related to loan spreads, but controlling for this does not eliminate the negative sin effect on spreads. Lastly, we control for organizational structure, following the theory that corporate diversification is negatively related to a firm's cost of capital. Our evidence is inconclusive regarding the effect of diversification on spreads.

The results in chapter 2 suggest that banks don't inherently care about social issues. When public scrutiny is not a concern, profit seems to be the sole driving force behind these institutions. Although this result may not come as a surprise, it is important to

question the true drivers of the recent initiatives of financial institutions and other firms towards more sustainable and social behavior. Is this change indeed what society needs, or is it simply "window dressing?"

Two major themes following the global financial crisis have been credit rating reliability and bank risk taking. Credit ratings play an important role in the financial sector, and their accuracy is an important factor to consider. After the crisis, rating agencies were heavily criticized for inflated ratings on risky securities in exchange for lucrative fees. According to Baghai, Becker, and Pitschner (2019) the use of credit ratings has not declined in the period from 1999 to 2017, rather it has increased. The authors conclude that this fact points to a lack of better alternatives. A recent article in the Wall Street Journal reiterates the role credit ratings played in the financial crisis, and the fact that these issues remain. The article states that a decade later, there is evidence [inflated ratings] persist as Credit Rating Agencies fight for market share (Podkul and Banerji, 2019).

Chapter 3 sets out to investigate the effect of credit ratings on syndicated loan prices. Although many of the articles referring to issues with credit ratings refer to the bond market, there is ample evidence that banks also use credit ratings in the syndicated loan market. We show, in line with previous research, that credit ratings explain a significant part of the syndicated loan prices we observe. The problem with credit ratings is that they are provided by different agencies, their methodologies are not entirely known to the market, and they don't always coincide, which results in what we call "split ratings". We show that when a borrower has two credit ratings, and they are split, the borrower pays a higher spread than the spread observed on a similar borrower with the same average rating. More importantly, we show that an individual borrower that moves from having a split rating to having a non-split rating experiences a lower spread, and vice versa. Podkul and Banerji (2019) argue that the regulatory remedy, competition among credit rating agencies, set forth to help alleviate issues observed with credit ratings seems to backfire. Similarly, Bolton, Freixas, and Shapiro (2012) model competition among Credit Rating Agencies and find that competition can reduce efficiency. The authors show that efficiency may be higher under a monopoly rather than a duopoly despite the potential for increased informativeness of two credit ratings.

The importance of syndicated loans, and their effect on interconnectedness, was illustrated during a speech by the then Federal Reserve Chairman Ben Bernanke at the Conference on Bank Structure and Competition in Chicago in May 2010: "We have initiated new efforts to better measure large institutions' counterparty credit risk and interconnectedness, sensitivity to market risk, and funding and liquidity exposures. These efforts will help us focus not only on risks to individual firms, but also on concentrations of risk that may arise through common exposures or sensitivity to common shocks. For example, we are now collecting additional data in a manner that will allow for the more timely and consistent measurement of individual bank and systemic risk exposures to

syndicated corporate loans." (Bernanke, 2010)

A response to the global financial crisis and the evident excessive risk taking by banks is Basel III, which builds on Basel II by including, among other things, specific standards on system-wide risks, by taking into account "the interlinkages and common exposures between financial institutions, especially for those deemed systematically important" (Caruana, 2010). The updated methodology published by the Bank of International Settlement (BIS) in 2013 to identify "Global Systematically Important Financial Institutions (G-SIFIs)," explicitly includes interconnectedness, but the syndicated loan market plays no material role in identifying the G-SIFIs (BIS, 2013). Regulation is however just one aspect in increasing the stability of the system. As Caruana (2010) argues, market discipline is an essential part of the puzzle to promote financial stability, and this responsibility lies with the financial industry, which includes banks, shareholders, investors and other market participants.

In chapter 4 we study the effect of interconnectedness on the value of the issuing bank. Previous research showed that the interconnectedness from syndicated loans is positively correlated to other measures of systemic risk. This chapter investigates whether market participants price this interconnection, or whether the negative aspects of the syndicated loan market are clouded by the positive aspects. The results show that prior to the demise of Lehman, and the financial crisis, markets did not price this risk. After these events however, markets seem to be aware of the risks. As a result, syndicated loans that significantly increase the level of interconnectedness are punished by the markets. Importantly, markets also recognize that signing syndicated loans, in and of itself, is not necessarily a bad thing. Our results show that market discipline, one of the important elements in financial stability as mentioned by Caruana (2010), is at work. We provide evidence that market participants recognize and punish banks that increase interconnectedness through syndicated loans.

To summarize, this dissertation shows that banks are, ultimately, pragmatic financial institutions. Loan provision is at the core of their business model, and information is at the core of loan provision. We don't find evidence that they are socially inclined, and appear to mainly price their assessment of the risk inherent in the borrowers. This is also reflected in their dealing with borrowers in the face of split ratings, where they are shown to be risk averse. Finally, we document that banks temporarily adjusted their syndicated loan network structure after the fall of Lehman, but quickly resumed business as usual when the economy settled down. Banks do little, if not for bucks.

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Research Impact

Two of the most pressing issues in the world are (i) climate change and (ii) the sustainability and stability of the global economy. In recent years, these two facets have become increasingly interlinked, with a strong push from both regulators and the public on companies and national economies to become 'greener.' Progress has been slow, but is gradually accelerating to a point where companies, particularly those in the public eye, are making real efforts towards sustainability.

Of course, the increased demand for sustainable practices is a business opportunity. Some companies take these opportunities and aim to actually offer sustainable products or services. Other companies put most of these investments towards the marketing budget, without making a real effort to improve their practices. The latter is often referred to as 'greenwashing' or 'window dressing,' the practice of making an unsubstantiated claim about the environmental or social benefits of a product or service.

The movement towards more environmentally friendly or sustainable services and practices has also reached the banking sector. Dutch examples include Triodos and ASN bank, who claim to be pioneers in "ethical banking." More recently, 130 international banks, amongst which many Dutch banks including ABN AMRO, ING, and Rabobank signed on to the "Principles for Responsible Banking', whose aim is "to help banks align their business strategies with society's goals" as set froth in the Paris Climate agreement (UnepFi, 2019). According to UnepFi (2019), "the Principles provide a framework for sustainable banking, and help the industry to demonstrate how it makes a positive contribution to society."

Chapter 2 of this thesis aims to investigate to what extent banks behave ethically, or sustainably, behind the scenes. That is, are these sustainable initiatives restricted to the consumer side of businesses that is visible to the public, or do they extend to the business-to-business operations of corporate lending? We analyze the interest rates firms pay on their large corporate loans, and in particular to what extent the rates differ for so-called "sin-firms," firms in the alcohol, tobacco, and gaming industry, from all other firms. Against all expectations, we find that banks actually charge these firms less than their non-sin counterparts, suggesting that the portrayed public image of banks differs from their actions. From a purely business standpoint, it is not entirely surprising; many of these industries will perform well in any economic climate, making them less risky. This does however not explain the full discount they receive. An important footnote is

that our sample ends in 2014, preceding the acceleration of the green and sustainable boom. However, we find no evidence that the discount has reduced as time progressed in our sample, which started in the 1980s.

The chapter highlights that we should be more critical of business practices in the financial industry. The rates set by the banks do not reflect the full cost to society, and consumer banking is only a small part of their full operations. Recent initiatives such as green bonds, the Equator Principles, and the 'Principles for Responsible Banking' are a step in the right direction, but generally, sustainability and banking are still two concepts which are hard to integrate.

The second major issue is the stability of the global economy, which has been an almost continues problem over the last decade. Starting with the financial crisis in 2008, followed by the European sovereign debt crisis around 2011, and more recently because of "Trumponomics" and Brexit. The severe magnitude of the first on this list was caused by underestimation of risk, and the resulting excessive risk taking of large financial institutions. When the risk materialized, Bear Sterns, and subsequently Lehman Brothers were insolvent, which triggered a worldwide financial crisis. In subsequent years, a regulatory push was made to address these shortcomings and prevent a similar event from occurring by the Obama administration. The Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) was introduced in 2010. Unfortunately, many of these regulations have been reversed in the relentless pursuit for economic growth. In 2018, a decade after the global financial crisis destabilized the US economy, the US House voted a regulatory rollback on Dodd-Frank, which significantly waters down the Obama-era rules governing the banking industry in search of greater stability (Rappeport and Flitter, 2018).

The European Commission is also actively working toward sustainable finance. One of the main examples of this is the EU High-Level Group on Sustainable Finance (HLEG). It is involved in steering capital flow toward sustainable investments, identifying steps necessary to protect the financial system from sustainability risks, and deploying these policies on a pan-European scale. Among the issues the HLEG focuses on are credit ratings. The report writes "CRAs are systemically important institutions, and their risk assessment methods influence the sustainability and stability of the financial system." The goal of the HLEG is to make the focus of these ratings less narrow and to include ESG information into credit ratings (European Commission, 2018).

Chapters 3 and 4 try to shed some light on some aspects of banks' role in these events. The former investigates how banks assess the risk of their borrowers, and the role large Credit Rating Agencies, such as Moody's and Standard & Poor's, play in this assessment. We find that banks strongly rely on these outside assessments. Given the inadequacy of their risk assessments preceding the financial crisis this is somewhat troubling.

The second of these chapters studies how the banks' core operations contribute to this risk. During the financial crisis, Lehman Brothers was injected with money by the gov-

ernment for the fear of a domino effect. The operations of banks are strongly intertwined through continuous collaborations, such that the failure of one bank may easily propagate to the next. We investigate one of these collaboration channels, the joint issuance of large corporate loans, and find that these offer a credible threat to financial stability. The loan portfolios of different banks are very similar, such that all banks may be faced with (the same) problems at the same time. After Lehman's failure, investors appear to be aware of this, and react strongly to large increases in this interconnectedness.

The two chapters highlight channels through which the bank impacts the economy beyond their own income statement. They play a crucial role in the economy and the risks they take therefore impact all of us.

Correspondingly, the analyses and conclusions put forth in this dissertation are of relevance to the broad public, but especially to regulators in charge of the banking sector's stability. Chapter 2 shows that banks are, almost naturally, primarily driven by pure profit motivations. Chapters 3 and 4 show that banks appear to have learned little from the financial crisis and have resumed their practices as before, some of which caused, or at least escalated, the crisis.

The conclusion is that banking still hardly looks beyond the bucks.

Biography

Judy Chalabi was born on November 1st, 1988 in El Haddadin, Lebanon, and grew up on Curaçao. She earned a B.Sc. in International Business from Maastricht University in 2010. In 2012, she received a M.Sc. in International Business from Maastricht University and an MA from Queen's University, Kingston, Canada.

After graduating, Judy joined the Department of Finance at Maastricht University to pursue a doctorate degree under the supervision of Prof. dr. Stefanie Kleimeier and Prof. dr. Rob Bauer. During her PhD she visited NYU Stern in the United States. The result of this effort is combined in this thesis.

In 2017, Judy joined the Department of Business Economics at Erasmus University Rotterdam as an Assistant Professor.