Systemic risk-taking at banks: Evidence from the pricing of syndicated loans*

Di Gong[†] Wolf Wagner[‡]

August 29, 2015

*We thank Thorsten Beck, Bo Becker, Jakob Bosma, Filippo De Marco (discussant), Bálint Horváth, Shiyang Huang, Harry Huizinga, Giuliano Iannotta, Bjorn Imbierowicz (discussant), Yongjun Kim (discussant), Iman van Lelyveld, Kebin Ma, Angela Maddaloni (discussant), Frédéric Malherbe, Kristoffer Milonas, Greg Nini, Matthew Osborne (discussant), Alberto Pozzolo (discussant), Maria Fabiana Penas, Yue Qiu, Rafael Repullo, Kasper Roszbach, Koen Schoors, Jie Zhang, Jean-Pierre Zigrand and participants in the seminars at the Hitotsubashi University, Bank of England, Systemic Risk Centre of LSE, Central University of Finance and Economics, Renmin University of China, European Banking Center, Tilburg University, 6th IFABS, NUS-RMI's 8th Annual Risk Management Conference, London Financial Intermediation Theory Workshop, 4th Emerging Scholars in Banking & Finance Conference at Cass Business School, SAEe 2014, RES postgraduate meeting 2015, the Conference on Macroprudential Regulation from Theory to Implementation at DNB, FIRS 2015, CICF 2015, ESWC 2015 and EFA 2015 for their valuable comments and discussions. Di is grateful to the hospitality of the Systemic Risk Centre at London School of Economics during his visiting in London. All errors are ours.

†Tilburg University. d.gong@tilburguniversity.edu.

‡Tilburg University and CEPR. w.wagner@uvt.nl.

Abstract

Public guarantees in the event of joint bank failures can result in systemic risk-taking and distort financing decisions of banks. We argue that the pricing of syndicated loans provides an ideal laboratory to study such distortions. In the absence of systemic risk-taking, non-diversifiability of aggregate risk implies that the compensation required for taking on aggregate risk is higher than for idiosyncratic risk. However, in the presence of public guarantees, banks have higher benefits from taking on aggregate risk as this leads to higher correlation across banks. Consistent with the latter, we find that banks charge lower lending interest rates for aggregate risk than for idiosyncratic risk, controlling for firm, loan and bank specific factors. Importantly, there is no evidence for systemic risk-taking for the sample of non-bank lenders who do not benefit from public guarantees. We also find that effect is larger for smaller and less correlated banks, consistent with higher a priori benefits from systemic risk-taking for such banks. The evidence provided suggests that public bail-out policies have significant ex-ante costs by distorting financing decisions in the economy.

JEL classification: G21, G32

Keywords: Public guarantees; Too-many-to-fail; Systemic risk-taking; Macroprudential regulation; Loan pricing

1 Introduction

Since the recent financial crisis is essentially a systemic crisis in which a large fraction of banking sectors failed simultaneously and incurred huge economic and social costs, systemic risk-taking at banks has become an important agenda for both policymakers and researchers. This paper aims to provide empirical evidence of banks' systemic risk-taking in the market of syndicated lending. Specifically, we document systemic risk-taking from the pricing of syndicated loan contracts. More importantly, we relate the incentive of banks' risk-taking to the "too-many-to-fail" bailout policy.

Banks may take systemic risk due to the fact that bank failure resolutions of regulatory agencies depend on whether the problem arises due to idiosyncratic or aggregate reasons (Acharya and Torulmazer, 2007). According to a review of the history of bank failures and resolution by Hoggarth, Reidhill and Sinclair (2004), in case of individual bank failure, regulators usually stand alone and seek private sector resolutions, such as merger and acquisition or liquidation. On the contrary, regulators often intervene in systemic crises in the forms of liquidity support, blanket guarantees or capital injections, when the cost of discontinuation of investment, fire sales and contagion outweighs the cost of bailout. The bailout in joint bank failures, or "too-many-to-fail" summarized in Acharya and Torulmazer (2007), may distort banks' incentives ex-ante when banks are aware of safety in similarity. Therefore, banks have strong incentives to make any problem a system-wide one and therefore maximize the likelihood of joint failure and hence collective bailout. A simple way for banks to take systemic risk is to expand aggregate exposure to the state of the economy. Essentially, banks can build up systemic risk at the balance sheet by investing in the aggregate risk in assets.

How can we learn about systemic risk-taking from the pricing of loans? In absence of systemic risk-taking, the compensation required for aggregate risk should be higher than (or at least as high as) the compensation for idiosyncratic risk[1]. This is because idiosyncratic risk is diversifiable (imperfectly though for banks, in contrast to stock investors). Hence lending rates for aggregate exposure should be higher than for idiosyncratic exposures. Suppose now that a "too-many-to-fail" bailout policy is in place, in which the regulator bails out banks if they fail jointly (Acharya and Yorulmazer, 2007). This provides incentives for banks to

[1]One reason to look at loan pricing is because there is a clear benchmark for different treatments of idiosyncratic and aggregate risks. For instance, CAPM is a typical pricing benchmark based on portfolio theory in absence of any distortion.

take on risks that make them more correlated. Taking on aggregate risk is the easiest way to become correlated as most banks can easily increase exposure to aggregate risk (by contrast, herding on for example a specific exposure, like a certain region, will be more difficult for banks)[2]. Thus, the "too-many-to-fail" guarantee provides a rationale for banks to charge lower lending rates for taking on aggregate risk relative to idiosyncratic risk. Evidence of lower lending rates for aggregate risk, after properly accounting for other factors, is thus evidence for systemic risk-taking at banks.

We empirically examine this question using a sample of the U.S. syndicated loans from Dealscan over the period 1988 to 2011. Adopting equity volatility of the borrower to proxy for the aggregate and idiosyncratic risks of the loan contract, we find that loan spreads are positively associated with borrowers' idiosyncratic risk whereas negatively associated with aggregate risk, controlling for borrower, loan and lender specific factors as well as year dummies. A one standard deviation increase in idiosyncratic risk raises the loan spread by 28 basis points, whereas a one standard deviation rise in aggregate risk lowers the lending rate by 5 basis points. Although the spread undercut on aggregate risk is not economically significant, the results imply that bank do not charge risk premium but rather offer lending rate discount to aggregate risk, which to some extent reveals the expected magnitude of the bailout subsidy a bank can obtain. Overall, the underpricing of aggregate risk relative to idiosyncratic risk can be taken as evidence of systemic risk-taking at banks. This pricing pattern is robust to risk measures of equity volatility estimated from CAPM regression and Fama-French three-factor regression. In addition, we show that such pricing patterns are not driven by borrowers' or lenders' unobserved heterogeneity as the results continue to hold when firm fixed effects or bank fixed effects are included.

Public guarantees in systemic crises apply largely to banks[3]. Non-bank lenders hence constitute an important control group. Consistent with systemic risk-taking driving the

[2]We are fully aware of the distinction between the two terms, systematic risk and systemic risk, as classified in Hansen (2012). Systematic risk is the aggregate risk which cannot be diversified away. Systemic risk refers to the risk imposed by interbank correlation that may bring down the entire banking industry. Still, the two concepts are intrinsically linked in our framework.

[3]Although large non-bank firms such as AIG, General Motors and Chrysler were also bailed out in the recent financial crisis, they accounted for a very small fraction of bailout recipients of the failed financial institutions. Therefore, the likelihood of being rescued by the public guarantee remains low for non-bank lenders. For the list of bailout recipients, please visit ProPublica http://projects.propublica.org/bailout/list. To track the list of bailout bank in the Capital Purchase Program, please visit http://money.cnn.com/news/specials/storysupplement/bankbailout/

results for the bank sample, we find that for the sample of non-bank lenders, lending rates are higher for aggregate risk consistent with the traditional portfolio theory. This provides strong evidence that results in the bank sample are driven by systemic risk-taking incentives. In addition, we address the concern of incomparable clients of banks and non-banks by applying the propensity score matching technique. Consistently, we find different pricing patterns in a matched sample of loans borrowed by similar firms but issued by banks and non-bank lenders.

An important motive for systemic risk-taking is the "too-many-to-fail" policy, which provides lowly correlated banks a rationale to become correlated in order to benefit from the bailout subsidy (Acharya and Yorulmazer, 2007). Consistent with this, interacting borrowers' aggregate and idiosyncratic risks with a market-based interbank correlation dummy, we find that less correlated banks charge lower spreads on aggregate risk relative to more correlated banks. When splitting the sample into two subsamples of highly and lowly correlated bank, we find only lowly correlated banks offer interest rate discounts on aggregate risk. The test of the impact of interbank correlations on loan pricing restricts the sample to publicly traded banks. To test the "too-many-to-fail" effect in a more general sample, we rely on bank accounting variables and test whether small banks are more aggressive in systemic risk-taking, a proposition in Acharya and Yorulmazer (2007). Interacting a bank size dummy with borrowers' aggregate and idiosyncratic risks, we find that smaller banks charge lower spreads on aggregate risk relative to larger banks, in line with the prediction of "too-many-to-fail" story. It is notably that the large banks require more compensation for both aggregate and idiosyncratic risks, different from the standard "too-big-to-fail" story.

This paper contributes to three strands of literature. First, in spite of fruitful studies on bank risk-taking in general (see Laeven and Levine, 2009; Keeley, 1990; Gropp, Gruendl and Guettler, 2013; Gropp, Hakenes and Schnabel, 2010; DeYoung, Peng and Yan, 2013; Altunbas, Gambacorta and Marqués-Ibáñez, 2010), the specific research on bank systemic risk-taking has been concentrated on theoretical models as it is challenging to empirically identify systemic risk-taking behaviors in the real world. This paper adds new empirical evidence of bank systemic risk-taking from the syndicated loan market. We illustrate systemic risk-taking from the underpricing of aggregate risk of loans, in contrast to Cai, Saunders and Steffen (2011) who document bank systemic risk-taking based on the interconnectedness of banks which is directly constructed from syndicated loan portfolios.

More broadly, this paper is related to the discussion of the impact of government guarantees on bank risk-taking. Banking theory suggests two opposite effects coexist. On the one hand, government support augments a bank's charter value and therefore discourages risk-taking (Keeley, 1990). On the other hand, public support mitigates market discipline as the incentive for investors to monitor the risk-shifting at the bank is reduced (Merton, 1977; Dam and Koetter, 2012; Gropp, Gruendl and Guettler, 2013; Brandao-Marques, Correa and Sapriza, 2012). Empirical studies present, however, mixed results, indicating that the net effect of government guarantees on risk-taking is ambiguous and depends on which effect dominates (Cordella and Yeyati, 2003). This paper adds new empirical evidence that the moral hazard effect of the government support dominates as banks protected by the "too-many-to-fail" guarantee tend to take systemic risk aggressively. This is related to the finding that suppoted banks charge lower loan spreads relative to a market benchmark by Gadanecz, Tsatsaronis, and Altunbas (2012).

Last, though the "too-many-to-fail" problem has drawn extensive attention in banking regulation especially since the recent financial crisis (Vives, 2011), empirical work testing this theory remains scarce. To the best of our knowledge, our paper is the first which unveils evidence of the ex-ante effect of "too-many-to-fail" that banks may intentionally extract bailout subsidies by taking systemic risk in expectation of the "too-many-to-fail" guarantee. Brown and Dinc (2009) is related to our paper, documenting evidence of the ex-post effect of "too-many-to-fail" that regulators are reluctant to close failed banks when other banks in the country are also weak.

Our empirical findings suggest large systemic risk-taking effect of public guarantees. Importantly, the findings unveil distortions as banks inefficiently underprice aggregate risk. Therefore, this paper has messages for public policy debate over banking regulation. First, banking regulation should focus on macroprudential regulation and operate at the collective level. Second, small and lowly correlated banks have been taking systemic risk aggressively and therefore need more regulator's attention.

The remainder of the paper is organized as follows. Section 2 sets out testable hypotheses. Section 3 presents the data, methodology and summary statistics. Section 4 examines evidence of bank systemic risk-taking from loan pricing. Section 5 analyzes the incentive for systemic risk-taking and highlights the importance of public guarantees. Section 6 tests the impacts of the "too-many-to-fail" guarantee on systemic risk-taking by examining the pricing patterns of banks of different interbank correlations and sizes. Section 7 concludes.

2 Hypotheses development

According to the portfolio theory, under the assumption of perfect diversification and no distortions, aggregate risk of the asset should be priced whereas diversifiable idiosyncratic risk should not. However, in the context of bank loans, idiosyncratic risk of the loans is likely to be priced but never more than aggregate risk for two reasons. First, most loan portfolios are imperfectly diversified or even limitedly diversified. Second, banks usually bear the losses from firm-specific defaults. However, if a bank expects to obtain bailout subsidies in a systemic crisis, then it may require lower compensation for aggregate risk relative to idiosyncratic risk as banks are less worried about losses in aggregate shocks in expectation of joint failure and collective bailout. Overall, distortions from the bailout policy lead banks to take systemic risk and underprice aggregate risk. This leads to the first hypothesis.

Hypothesis 1: *Banks require lower loan spreads for aggregate risk relative to idiosyncratic risk, indicating systemic risk-taking.*

Public guarantees can be a candidate for driving systemic risk-taking at banks. Since bailout guarantees are challenging to measure or proxy in a direct way, we use the presence (or absence) of public guarantees over banks (non-bank lenders) to test the impact of guarantees on risk-taking. In particular, banks are protected by explicit or implicit public guarantees that regulators and government will support them in a systemic crisis in the forms of capital injection or liquidity support. Hence banks could have incentives to take systemic risk. On the contrary, non-bank lenders which are not protected by any public guarantee should have no incentive to take systemic risk and therefore charge higher spreads for aggregate risk. Taken together, we propose the following hypothesis.

Hypothesis 2: *Non-bank lenders which are not protected by public guarantees do not take systemic risk and require higher loan spreads for aggregate risk relative to idiosyncratic risk.*

Acharya and Yorulmazer (2007) model the "too-many-to-fail" problem that a bank regulator finds it ex-post optimal to bail out failed banks when the number of failures is large, whereas the probability of the collective bailout is low when the number of bank failures is small, as failed banks can be acquired by surviving banks. The ex-post optimal bailout exists in the circumstance that the misallocation cost of liquidating bank assets to outside investors in case of systemic banking crisis exceeds the cost of injecting funds. Therefore, the bailout expectation creates incentives for banks to herd ex-ante in order to maximize the likelihood of failing together and therefore collective bailout. To test that systemic risk-taking is driven by the "too-many-to-fail" guarantee, we predict less correlated banks may be more aggressive in taking systemic risk as the marginal benefit of increased systemic risk could substantially raise the likelihood of joint failure and hence the collective bailout subsidy.

Hypothesis 3: *Less correlated banks take systemic risk more aggressively relative to more correlated banks.*

To corroborate the argument of "too-many-to-fail" effect, we predict smaller banks charge lower lending rates to aggregate risk, based on the prediction that smaller banks have stronger incentives to take systemic risk in Acharya and Yozulmazer (2007), different from the "too-big-to-fail" effect. This is because that the bailout subsidy increases in the systemic risk-taking for small banks when big banks also fail but it does not increase for big banks when small banks fail as big banks can acquire failed small banks (Acharya and Yorulmazer, 2007)

Hypothesis 4: *Smaller banks take systemic risk more aggressively relative to larger banks.*

3 Data, Methodology and Summary Statistics

3.1 Data

Syndicated loans provide an ideal laboratory to test systemic risk-taking at banks. First, syndicated loans are a vital source of corporate finance for large U.S. corporations (Sufi, 2007; Becker and Ivashina, 2014) and represent a substantial fraction of bank loan portfolios (Ivashina, 2009). Second, for each loan contract Dealscan provides rich information about the identities of borrowers and lenders which allow me to control for a variety of borrowers' and lenders' characteristics. Specifically, we can study how the characteristics of the banks (investors) of loans (assets) may affect the pricing. Last, non-bank lenders which are active in the syndicated loan market but are unprotected by bailout policies naturally constitute a control group for our test of the impact of public guarantees on systemic risk-taking.

Obtaining syndicated loan data from LPC Dealscan, we focus on U.S. firms borrowing from

U.S. banks over the period between 1988 and 2011[4]. We exclude loans borrowed by companies in the financial sector from the sample (SIC codes 6000 to 6400, Finance and Insurance). Syndicated loans are usually structured in a number of facilities, also called tranches. We treat facilities in each deal as different loans because spreads, identity of lenders and other contractual features often vary within a syndicated loan deal[5]. Therefore, each observation in the regressions corresponds to a syndicated loan facility.

By merging Dealscan with Compustat, we have detailed annual accounting information of the borrowers[6]. Compustat provides annual report data of publicly listed American companies, of which information problems are generally less severe than privately held firms.

In addition, we restrict our sample to loans taken out by companies of which stocks are actively traded because the proxies for idiosyncratic and aggregate risks are constructed based on stock market information. To calculate the equity volatility of borrowers, we collect daily stock return data from CRSP over the year leading up to the facility activation date for borrowers listed in NYSE, AMEX and NASDAQ[7]. We drop out borrowers with less than 100 trading days available in the event window[8]. Moreover, we collect Fama-French Factors from Wharton Research Data Services (WRDS).

Though our analysis of systemic risk-taking assumes a loan is made by a single lender, most of loans in our sample are syndicated by a number of leader arrangers and participants. This is less of a problem given our focus on the characteristics of lead arrangers. According to Dennis and Mullineaux (2000), Sufi (2007) and Santos and Winton (2008), leader arrangers are delegated to collect information and monitor the borrower on behalf of the syndicate[9]. In addition, leader arrangers set lending rates and non-pricing loan terms. By contrast,

[4]Before 1987, the coverage of Deanscan is uneven. For an overview of the Dealscan database, see Strahan (1999).

[5]This is a common practice in the loan pricing literature. See similar analyses in Carey and Nini (2007), Focarelli, Pozzolo and Casolaro (2008), Santos (2011), Gaul and Uysal (2014).

[6]We are indebted to Sudheer Chava and Michael Roberts for providing the link between Dealscan with Compustat, see Chava and Roberts (2008).

[7]We link LPC Deanscan with Compustat via GVKEY. Next, we use PERMNO to link Compustat with CRSP.

[8]Campbell and Taksler (2003) argue that a fairly long event window is required to measure the volatility that is publicly observed by corporate bond investors.

[9]Dealscan indicates the role of each lender. We follow the classification rule in Cai, Saunders and Steffen (2011). If the variable *LeadArrangerCredit* indicates "Yes", a lender is classified as a lead arranger. We correct for the role of lenders of loans that *LeadArrangerCredit* indicates "Yes" but "LenderRole" falls into participants as non-lead arrangers. In addition, if no lead arranger is identified, we treat a lender as a lead arranger if its "LenderRole" is classified as following items: Admin agent, Agent, Arranger, Bookrunner, Coordinating arranger, Lead arranger, Lead bank, Lead manager, Mandated arranger, Mandated Lead arranger.

participants play a rather passive role in the syndicate. Therefore, it is a reasonable assumption that the lead arranger plays the role of the single bank lender in bilateral corporate lending of assessing the credit worthiness of the borrower and making decisions on risk-taking. Moreover, we restrict our sample to loans originated by a single lead arranger and exclude loans originated by multiple lead arrangers in order to clearly capture the effect of the lender's characteristics on loan pricing[10]. We manually match lead banks in Dealscan with commercial banks in Call reports, depending on bank names, geographical locations and operating dates. We complement the unmatched sample of banking holding companies with Federal Reserve Y-9C reports. Additionally, we control for mergers and acquisition by matching the loan of the acquired lender to the accounting information of its acquirer.

To calculate the stock market based measure of interbank correlation, we collect banks' daily stock return data from CRSP one year preceding to the quarter of loan origination and the S&P 500 banking sector index from Datastream dating back to the last quarter of 1989. We link bank stock return with Call Reports and FY Y9C using the CRSP-FRB link from the Federal Reserve Bank of New York. In particular, we match commercial banks that are subsidiaries of the listed bank holding companies with the stock return data of their parent companies, similar to Lin and Paravisini (2012).

3.2 Loan pricing model

In the empirical analysis, we estimate the following loan pricing model:

$$\begin{aligned} LoanSpread_{i,f,b,t} =& c + \alpha_1 IdioVol_{i,t-1} + \alpha_2 AggVol_{i,t-1} + \sum_j \gamma_j \mathbf{Firm}_{i,j,t-1} \\ &+ \sum_k \theta_k \mathbf{Loan}_{f,k,t} + \sum_n \psi_n \mathbf{Bank}_{b,n,t-1} + \sum_t \delta_t T_t + \epsilon_{i,f,b,t} \end{aligned} \tag{1}$$

where f, i, b and t denote facility, firm, bank and year, respectively. The dependent variable, *LoanSpread*, is the all-in-drawn spread in Dealscan which denotes an interest rate spread over LIBOR measured in basis points. It is summarized by Dealscan as a measure of overall costs of the loan, accounting for both one time and recurring fees. *IdioVol* and *AggVol*

[10] It makes little sense to aggregate lenders' characteristics (both leader arranger and participants) for loans with multiple lead arrangers. Nevertheless, our baseline results hold for loans granted by multiple lead arrangers.

represent idiosyncratic and aggregate risks, respectively[11]. Moreover, we include firm specific variables ($\mathbf{Firm_i}$), loan specific variables ($\mathbf{Loan_f}$) and bank specific variables ($\mathbf{Bank_b}$). We also include year dummies T throughout all specifications. ϵ is the error term. We estimate the baseline loan pricing model by cross-sectional OLS regressions that pool together all valid observations. Robust standard errors are clustered at the lender level to correct for correlation across observations of a given lender, though the results hold when clustering at the levels of borrowers or the pairs of borrower-lender.

To compute the key independent variables, idiosyncratic and aggregate risks of the borrower, we rely on the borrower's equity volatilities which are forward-looking and are driven by market information. The idea is that we can think of the holder of risky debt as the owner of riskless bonds who have issued put options to the holder of firm equity (Merton, 1974). The strike price equals the face value of the debt and reflects limited liability of equity holders in the event of default. Increased equity volatility raises the value of put option, benefiting the equity holder at the expense of the debt holder. Hence a firm with more volatile equity is more likely to reach the bound condition for default. In addition, there is a burgeoning literature that applies equity volatility to explain credit spreads. In a seminal paper Campbell and Taksler (2003) find evidence that equity volatility, especially idiosyncratic equity volatility, has substantial explanatory power for corporate bond yields. Zhang, Zhou and Zhu (2009) and Ericsson, Jacob and Oviedo (2009) apply the same logic to credit default swap (CDS) pricing and find equity volatility is an important determinant of CDS spreads. Equity volatility has also been applied in empirical banking literature. Gaul and Uysal (2013) relate total equity volatility with loan spreads to explain the "global loan pricing puzzle" in Carey and Nini (2007). Santos and Winton (2013) use stock volatility as a proxy of the borrower's default risk. Acharya, Almeida and Campello (2013) also use equity beta to explain the cost of credit lines.

To decompose borrowers' equity volatility into idiosyncratic and aggregate components to proxy idiosyncratic and aggregate risks, respectively, we run a standard CAPM regression as

[11] We do not include credit ratings of the borrower. The reason is that in principle credit rating should perfectly capture the default risk and therefore both idiosyncratic and aggregate risks would enter the regression insignificantly.

follows:

$$r_{i,d} - r_d^f = \beta_{i,d}^{CAPM} \times (r_d^m - r_d^f) + \epsilon_{i,d} \tag{2}$$

where $r_{i,d}$, r_d^m and r_d^f represent individual stock daily return, market return calculated as the value-weight return on all NYSE, AMEX, and NASDAQ stocks in CRSP and risk free return proxied by the one-month Treasury bill rate, respectively. We define the idiosyncratic volatility as standard deviation of the residual, $IdioVol^{CAPM}$=$SD(\epsilon)$. In addition, we define the aggregate risk as the product of beta and market volatility, $AggVol^{CAPM}$=$\beta^{CAPM} \times MarketVol$, where $MarketVol$ is the standard deviation of market excess return ($SD(r^m - r^f)$).

Alternatively, we adopt Fama French three-factor model (Fama and French, 1993) using the following regression:

$$r_{i,d} - r_d^f = \alpha_{i,d} + \beta_{i,d}^{MKT} \times MKT_d + \beta_{i,d}^{SMB} \times SMB_d + \beta_{i,d}^{HML} \times HML_d + \varepsilon_{i,d} \tag{3}$$

Where the market factor MKT_d is the value-weight return on all NYSE, AMEX, and NASDAQ stocks from CRSP minus the one-month Treasury bill rate, the size factor SMB_d is the average return on the three small portfolios minus the average return on the three big portfolios, the value factor HML_d is the average return on the two value portfolios minus the average return on the two growth portfolios, respectively. We stick to the standard deviation of the residual $IdioVol^{FF} = SD(\varepsilon)$ as the idiosyncratic volatility. On the other hand, following Bali, Brown and Caglayan (2012) we define the aggregate risk in the multifactor model as the total volatility that is attributable to Fama French factors and the factors' cross-covariances, $AggVol^{FF} = \sqrt{(TotalVol)^2 - (IdioVol^{FF})^2}$. In the end, we annualize all equity volatilities by a multiplier of $\sqrt{252}$ as daily stock returns are used.

We include a number of firm level controls that may affect the lending interest rates. Log(Sales) is the logarithm of the firm's sales at close in millions of dollars. Larger firms are more informationally transparent, therefore we expect larger borrowers have lower spreads. Next, LEVERAGE is a ratio of total debts to total assets. Highly leveraged firms are more likely to default and hence are expected to be charged a higher lending rate. Besides, we control for PROFMARGIN which is defined as a ratio of profit margin to firm sales, and ROA which is return on assets, to measure the performance and profitability of the borrower.

As a highly profitable firm is safer and less likely to fall into financial distress, it should be charged a lower spread. As for the firm specific controls that affect loss given default (LGD), we include new working capital and tangibles assets. NWC measures a ratio of net working capital to total assets. Firms with more net working capital are expected to lose less value in the event of default. In addition, TANGIBLE measures a fraction of tangible assets to total assets. Borrowers with a higher fraction of tangible assets are more informationally transparent (Morgan, 2001) and have higher values in the event of default as the value of intangible assets are much volatile. Therefore we expect a lower spread on the loans taken out by borrowers with a higher fraction of tangible assets. We control for Market-to-Book ratio, MKTBOOK, an imperfect proxy of Tobin's q, which is a ratio of the market value of a firm to its accounting value. We expect a firm with a higher Market-to-Book ratio to have lower spreads. Finally, we include industry dummies that classify borrowers into ten sectors based on 4-digit SIC codes, considering that loss given default (LGD) is strongly correlated with industry characteristics (Hertzel and Officer, 2012; James and Kizilaslan, 2014). Our results hold if we alternatively use dummy variables for two-digit SIC industry groups.

Even though nonpricing loan specific variables are jointly determined with loan spreads and therefore are endogenous, we include these contractual terms. We include Log(FacilitySize), measured by the log of the facility amount in millions of dollars. Large loans are likely to be associated with greater credit risk in the underlying project and lower liquidity, but could also be borrowed by larger firms which have more cushions against adverse shocks. Therefore, the impact of loan size on loan pricing is not unambiguous. Additionally, we include MATURITY which is the maturity of the facility in years. The effect of maturity on loan spreads is also ambiguous. Next, we use the number of lenders in a facility (#Lenders) and the number of facilities within a deal (#Facilities) to proxy the syndicated structure. To measure the liquidity exposure of each facility, we classify a loan as a line of credit (REVOLVER) or a term loan (TERMLOAN)[12]. Moreover, we include dummy variables that indicate whether a loan is senior (SENIOR) in the borrowers' liability structure and whether the loan is secured by collateral (SECURED). Seniority and collateral may reduce the lenders' loss in the event of borrower default and therefore reduce lending rates, however, the contractual arrangement

[12] In particular, a loan is classified as a revolver is the loan type is expressed in Dealscan as "364-Day Facility", "Revolver/Line < 1 Yr.", "Revolver/Line >= 1 Yr.", "Revolver/Term Loan", "Demand Loan", "Limited Line". Alternatively, a loan is defined as a term loan if the loan type is recorded as "Term Loan", "Term Loan A", "Term Loan B", "Term Loan C", "Term Loan F", "Delay Draw Term Loan".

may be required ex-ante to protect lenders towards specifically risky borrowers. Therefore, the relation between seniority, collateral and loan pricing is an empirical question. Last, we control for loan purpose dummies into five categories: Corporate Purpose, Debt Repayment, Takeover, Working Capital and Other.

As the loan contract is negotiated between the borrowers and lenders, lenders' characteristics may also affect contract terms and have been incorporated into the analysis of loan pricing recently. Analyzing the effect of banks' financial health on loan spreads, Hubbard, Kuttner and Palia (2002) find less capitalized bank charge higher spreads than well capitalized banks. Examining how bank capital, borrower cash flow and their interaction affect loan pricing, Santos and Winton (2013) show that less capitalized banks charge relatively more for borrowers with low cash flow but offer discounts for borrowers with high cash flow. Santos (2010) emphasizes the impacts of bank losses on loan contracts. He shows evidence of credit crunch in the subprime crisis that even though firms paid higher loan spreads and took out smaller loans during the subprime crisis, the increase in loan spreads was higher for firms that borrowed from banks that incurred large losses. In this study we consider following bank specific variables of lead arrangers. First, we include SizeBK as the logarithm of bank total assets in millions of dollars. Large banks usually have diversified portfolios and good risk management, therefore we expect large banks charge low lending rates. Next, we control for CapitalBK, denoted as a ratio of bank capital to total assets. Well capitalized banks have more capital buffer and therefore are expected to charge a lower spread. In addition, we use NPLBK, a ratio of nonperforming loans to total assets, as a measure of bank credit risk. Risky banks may charge additional compensation for undertaking extra risk. Hence, we expect banks with a higher proportion of nonperforming loans to charge a higher spread. We also use ZscoreBK as a direct measure of bank insolvancy risk. We calculate Z score following Laeven and Levine (2009) but use an eight-quarter rolling window. Moreover, we include a bank profitability measure ROABK. More profitable banks are expected to charge a lower rate. To control for the impact of bank liquidity on loan rates, we include LiquidityBK to measure the liquidity of bank assets, which is a ratio of sum of liquid securities and cash to total assets. Besides, we use the growth rate of loans (LoanGrowthBK) to measure investment opportunities of the lender. In the end we include CostOfFundBK which is total interest expenses over total liabilities to measure funding costs.

In particular, we use the accounting information of the borrower and lenders from the fiscal year ending in the calendar year $t-1$ for loans made in calendar year t. To eliminate the bias from outliers, we winsorize loan spreads, firm and bank specific variables and borrowers' equity volatilities at 1 and 99 percentile levels[13]. We include year dummies to capture time trends throughout the analysis as Santos (2011) has shown the business cycle effect on loan contracts.

3.3 Summary Statistics

The final sample consists of 11,323 facilities taken out of 4,192 publicly listed U.S. nonfinancial firms from 464 U.S. lead banks over the period 1988 to 2011. Table 1 presents summary statistics of the sample. The average all-in-drawn spread is 207 basis points over LIBOR. The average CAPM idiosyncratic volatility is 0.554, very close to the mean of total volatility. Since market is usually relatively stable, the average aggregate volatility which is the product of Beta and market volatility is rather small (0.116), much smaller than the average beta (0.758). It is worth noting that aggregate volatility could be negative as the beta of some borrowers is negative. Overall, the idiosyncratic and aggregate volatilities estimated from CAPM and Fama French three-factor models are quite similar.

Looking at firm level controls, we find the average log of firm total assets is 5.611. The mean of borrowers' leverage is 28.035%. The profit margin is highly skewed, with a mean of -0.871% and a median of 3.211%. The mean of net working capital to total assets and tangible assets to total assets are 21.107% and 69.036%, respectively. The average Market-to-Book ratio is 1.782.

We turn to the loan controls in the sample. The average logarithm of facility amount is 3.805. It is worth noting that the log of facility size can be negative when the loan is pretty small. Syndicated loans in the sample have an average maturity of 3.589 years. In addition, on average each syndicate has 6 lenders and is structured into 1.763 facilities. Looking at the loan types, 73% of loans are lines of credit while 24% are term loans. Almost all loans are senior in the borrower's liability structure. In the end, 75% of loans are secured by collateral.

We check the sample characteristics of banks. Except bank size and z score which are log adjusted, the rest bank specific variables are expressed in ratios. Banks are much larger as the

[13]See Appendix Table A1 for detailed information of variables.

average log of bank total assets is 11.269. The average equity to asset ratio is 7.524%. Both the average share of nonperforming loans to gross loans and the average ROA are 0.952%. The mean of bank Z score is 3.179. Liquid assets account for 18.716% of total assets. The median of loan growth rate is 9.191% although the average is rather high at 20.476%. The average bank has the cost of funds at 3.390%. As not all banks are listed and traded in stock exchanges, we have the information of interbank correlation for approximately 9321 facilities, of which the average interbank correlation is 0.735.

4 Evidence of bank systemic risk-taking from the pricing of idiosyncratic and aggregate risks

In this section, we apply the baseline loan pricing model to examine bank systemic risk-taking. Table 2 reports the results using idiosyncratic and aggregate risks estimated from the CAPM regression. In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. In column 1, we regress loan spreads on equity volatilities and year dummies only. The coefficient of the idiosyncratic volatility is positive and significant, indicating banks charge risk premium for bearing idiosyncratic default risk of the borrower. On the contrary, the coefficient of aggregate risk is negative and significant, suggesting that banks do not charge risk premium but rather offer lending rate discounts to aggregate exposure, consistent with hypothesis 1 that banks take systemic risk. In column 2, the main results are insensitive to the inclusion of firm level balance sheet variables and industry dummies[14]. In addition, the firm characteristics have expected signs and are mostly significant. In particular, we find that larger firms, firms with higher profit margins, and less leveraged firms pay lower loan spreads. Proxies for net working capital and tangible assets have expected signs and are statistically significant. The market to book ratio is marginally significant and negatively associated with loan spreads. In column 3 we further control for loan specific variables, despite that loan spreads and other contract terms are simultaneously determined. The hypothesis 1 continues to be supported. Moreover, we find that larger loans and loans with longer maturity are charged at a higher rate. The two proxies of syndicate structure have opposite effects. In

[14]The number of observations in the regressions drops due missing values in industry classification.

particular, loans of more lenders in the syndicate are associated with lower spreads, whereas loans with more facilities are more expensive. Moreover, lines of credit are generally cheaper. A loan is much cheaper if it is senior when it ensures the priority of the lender to claim to residual value in the event of borrower bankruptcy. Furthermore, a secured loan is charged a higher spread than a similar one without collateral probably because only risky borrowers are required for collateral and are ex-ante charged a risk premium. In column 4, we add bank level controls, provided that the lender' characteristics may have impacts on loan pricing. As a result, our main results of systemic risk-taking continue to hold. Specifically, banks do charge a sizable spread on idiosyncratic risk. A firm of which idiosyncratic risk is one standard deviation (0.303) greater than the sample mean pays 28 ($= 91.778 \times 0.303$) basis points extra. By contrast, a one standard deviation (0.101) increase in the aggregate risk lowers the loan interest rate by 4 ($= -42.850 \times 0.101$) basis points. Though the spread undercut on aggregate risk is not economically significant, it indicates that banks do not charge risk premium to cover the potential losses to aggregate shocks. Furthermore, we find that larger banks, well-capitalized banks, banks with high costs of funding and banks with high loan growth rates charge lower spreads while risky banks charge relatively higher spreads.

We do the same exercise using equity volatilities estimated from the Fama French three-factor model in Table 3. Overall, all estimates preserve the sign, significance and magnitude with the baseline results using CAPM equity volatility. Again, the results hold when standard errors are clustered at the bank level (or firm-bank pair level) to correct for correlation across a given bank (bank-firm pair). For brevity, in the following output tables we do not report the estimated coefficients of firm, loan and bank specific control variables.

Table 4 shows that our results are insensitive to various alternative estimates of idiosyncratic and aggregate risks. Even though equity beta is not comparable to volatility, we use CAPM beta ($Beta^{CAPM}$) and market beta in the Fama French three-factor model ($Beta^{MKT}$) as alternative measures of aggregate exposure. We find similar evidence that banks charge lower spreads for aggregate risk in columns 1 and 2. In addition, controlling for both total volatility ($TotalVol$) and a share of aggregate volatility in total volatility ($AggVol^{CAPM}/TotalVol$, $AggVol^{FF}/TotalVol$) as key explanatory variables in columns 3 and 4, we find that the coefficient of total volatility is positively and significantly associated with lending rates, whilst the coefficient of aggregate volatility enters negatively and significantly.

The use of equity volatility in our analysis relies on a crucial assumption that equity volatility captures the credit risk associated with the unobserved firm asset volatility. However, contingent claims model suggests equity volatility is a complex function of both asset volatility and leverage. A caveat may arise if, although leverage is a source of firm-specific credit risk, it can amplify or weaken the asset volatility effect and therefore contaminate the estimated effect of equity volatility (Campbell and Taksler, 2003; Gaul and Uysal, 2013). For instance, Campbell and Taksler (2003) argue that debt holders of a company with a very small amount of debt are not worried about insolvency even if the equity is volatile. To better capture the credit risk, we deleverage equity volatility as in James and Kizilaslan (2014) by a multiplier of equity/(debt+equity), in which equity is the borrower's market capitalization and debt is the sum of short term debt and half of long term debt. We report the results in the last two columns where the unlevered equity volatilities yield similar results to our baseline regressions. In particular, the coefficient of unlevered aggregate volatility remains significant and negative, continuing to support our hypothesis.

The baseline specification may be prone to omitted variable bias if unobserved firm characteristics drive both firm's equity volatility and loan spreads. We restructure the data set into panel data in which we have the cross section unit, i=firm, and the time series unit, f=facility. We estimate a firm fixed effects model, allowing for arbitrary correlation between the unobserved borrower effect and the observed explanatory variables. The identification comes from variations in equity volatility and loan spreads within the same firm. In particular, we compare loan spreads of the same firm across different loans when equity volatilities differ before the loan origination. The results in the first two columns of Table 5 further confirm the findings that idiosyncratic volatility is positively priced and aggregate volatility is negatively priced. The weak significance of aggregate volatility is the result of a short dimension along facilities within the borrower as each firm borrows on average 2.7 facilities in the sample[15].

Likewise, another caveat would arise if unobserved bank characteristics might be correlated with lending interest rates. For instance, showing that a bank's stock performance during the 1998 crisis predicts the stock performance and probability of failure in the recent financial crisis, Fahlenbrach, Prilmeier and Stulz (2012) suggest that banks' business model or risk culture may be persistent over time. The unobserved business model or risk culture may

[15] The information loss arising from the short times series dimension for each cross section unit may weaken the identification in panel data estimations.

have a non-negligible impact when the bank decides the loan interest rates. To rule out the effect of unobserved bank characteristics on pricing patterns, we reorganize the sample into panel data in which b=bank is the cross-section unit and f=facility is the time series unit. We estimate a bank fixed effects model that eliminates the unobserved bank specific effects which are heterogenous across lenders but are constant over facilities of the same lender. Our results largely hold in Columns 3 and 4. The highly statistical significance comes from the fact that each bank lends on average 30 facilities in the sample.

Taken together, we find that loan spreads are positively associated with idiosyncratic risk but negatively associated with aggregate risk of the borrower. The lending rate discount to aggregate risk can be interpreted as evidence of systemic risk-taking in syndicated loans. In the next section, we investigate the incentives for banks taking systemic risk.

5 Systemic risk-taking and public guarantees: Do non-bank lenders take systemic risk as well?

Although non-bank institutional investors have been actively participating in the syndicated loan market especially in the leveraged loan segment since 2000, loans originated by non-bank lenders to publicly traded U.S. nonfinancial companies remained substantially fewer than similar bank loans[16]. We collect 1789 loans originated by non-bank institutional investors, for instance, finance companies, corporations, mutual funds, trust companies, insurance companies and so forth, which are not protected by public bailout guarantees[17]. For comparison, we collect bank loans originated by commercial banks, bank holding companies, thrifts, savings and loan associations (S&Ls). Because the status of investment banks and mortgage banks are ambiguous in bailouts in a sense that they are not strictly protected by public guarantee ex-ante but often obtain government support ex-post in a systemic crisis, we exclude the two types of lenders from the sample. Table A2 displays the composition of our sample. One can see the majority of the non-bank loans come from finance companies.

We report the regression output for the loan pricing patterns by non-bank lenders and bank lenders in Table 6. As the accounting information for non-bank lenders is not as readily accessible as banks, we only control for borrower and loan specific variables as well as year

[16] For descriptions of the role of non-bank lenders in the syndicated loan market, see Ivashina and Sun (2011).

[17] None of the four insurance companies in our sample, Equitable Life Assurance Society of the US, Prudential Insurance Co of America, Northwestern National Life, New York Life Insurance Co, are bailout recipients.

dummies[18]. We find that both aggregate risk and idiosyncratic risks are priced similarly by non-bank lenders in columns 1 and 3. In particular, the estimated coefficient for aggregate risk is positive, significant, and slightly greater that the coefficient of idiosyncratic risk, in line with the prediction of the portfolio theory. In other words, non-bank lenders charge a risk markup for aggregate risk in the absence of public guarantees. In columns 2 and 4 the main results that banks charge lower lending rates to aggregate risk still hold. Overall, given that banks provide lending interest rate discounts to aggregate risk whereas non-bank lenders charge a significantly positive risk premium for aggregate risk, we conclude that the key distinction between the two cohorts of lenders, namely, the coverage of public guarantees, determines pricing patterns and systemic risk-taking at banks.

One concern may arise that our finding of the different pricing patterns of bank and non-bank loans could be the result of spurious correlation. For instance, banks serve observably less risky borrowers whereas non-bank lenders especially finance companies cater to observably more risky firms (Carey, Post and Sharpe, 1998). This is indeed reflected in our sample. The first three columns of Table 8 summarize the firm-specific covariates of loans originated by banks and non-bank lenders, respectively. The t-tests of the sample means suggest that non-bank lenders serve borrowers which have higher idiosyncratic stock volatility, smaller size, higher leverage and lower profitability.

Although this lending specialization may be one omitted driver of pricing discrepancy, this caveat is unlikely to bias our findings for two reasons. First, estimating the loan pricing models for the subsamples of bank loans and non-bank loans separately could control for this possibility. Second, even if lending specialization affects the selection of the riskiness of borrower and therefore loan rates, it can only explain why non-bank lenders charge positive loan spreads on both idiosyncratic and aggregate risks to risky borrowers. Albeit it cannot explain the lending rate discount by banks without the introduction of banking regulation, particularly bailout subsidies.

Nevertheless, matching techniques could be introduced to address this concern of selection on observables, namely, lenders may select their clients based on borrowers' characteristics (Tucker, 2010). In particular, we can address the issue of imperfect comparability of bank and non-bank borrowers by employing propensity score matching. We take the pool of loans by

[18]The number of bank loan observations is greater here than in the baseline regression because we avoid attrition in the procedure of matching loans with bank accounting variables.

non-bank borrowers as the treatment group and search for a control group of loans by bank borrowers which are similar to non-bank borrowers in all dimensions (based on observable firm controls).

When applying the propensity score matching algorithm, we first estimate a Probit model to predict the likelihood of a firm to borrow from a non-bank lender. Therefore, the dependent variable is a dummy which takes 1 if the loan is originated by a non-bank lender, and 0 if by a bank. The Probit regression includes idiosyncratic and aggregate risks, firm-specific controls, industry dummies, and year dummies[19]. Robust standard errors are clustered at the lender level. The results are presented in column 1 of Table 7, which indicates idiosyncratic risk, leverage, profitability and market-to-book value have significant impacts on the probability of borrowing from a non-bank lender. The p-value of χ^2 test of the model fitness of 0.000 suggests that before matching, firm-specific variables can explain a significant amount of variations in the choice of lenders. Next, we use the propensity score to perform a nearest-neighbor propensity score matching. To avoid bad matches, we impose a tolerance level of 0.05% on the maximum propensity score distance allowed. In the end, each loan originated by a non-bank lender is matched to a loan in the control group with the closest propensity score in terms of the borrowers' characteristics. We end up with 1549 pairs of matched loans[20].

Since our identification depends crucially on the conditional independence assumption, which assumes after matching the choice of lender type is randomly assigned, we conduct two diagnostic tests to verify this assumption holds. First, we re-estimate the Probit model restricted to the matched sample in column 2 of Table 7. None of the explanatory variable is significant. Moreover, the p-value of the χ^2 test is 0.998, suggesting that we cannot reject the null hypothesis that all of the estimated coefficients are zero. This supports the validity of conditional independence assumption in the matched sample. Second, we conduct the univariate comparisons of firms' characteristics after matching in the last three columns of Table 8. None of the observable differences of the borrowers is statistically significant. Overall, the diagnostic tests assure that propensity score matching yields a matched sample which is

[19]We are unable to match, however, on the lenders' characteristics which are partially unobservable for the group of non-bank lenders.

[20]The number of matched loan is smaller than in Table 6 as we impose common support restriction which drops treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls, and trim (5%) which drops 5% of the treatment observations at which the propensity score density of the control observations is the lowest. The two restrictions substantially improve the quality of matching.

more homogenous and less prone to selection bias.

We re-estimate our non-bank versus bank tests in Table 9. Despite a drop in sample size, we obtain similar results as in Table 6.

6 Too-many-to-fail

We directly test the "too-many-to-fail" argument by assessing the impact of interbank correlations on loan pricing. The idea is that less correlated banks have stronger incentives to increase interbank correlation and therefore take systemic risk in order to maximize the likelihood of failing together with systemically important banks. Therefore "too-many-to-fail" argument predicts that less correlated banks charge lower spreads to aggregate risk compared to more correlated banks[21]. To measure interbank correlations, we first calculate the correlation of the bank's daily excess return with the S&P 500 banking sector index using the data one year prior to the quarter of loan origination. Since the data of S&P 500 banking sector index start from the Q4 1989, the sample consisting of 9 321 loans taken out by 3562 firms from 259 publicly listed banks, is slightly shorter and smaller than the one used in the baseline analysis. We construct a dummy variable $LowCorrBK$ that equals one if a bank's interbank correlation is smaller than the median value and zero otherwise. Interacting the bank correlation with borrowers' equity volatilities, we estimate the following model:

$$\begin{aligned} LoanSpread_{i,f,b,t} =& c + \alpha_1 IdioVol_{i,t-1} + \alpha_2 AggVol_{i,t-1} + \alpha_3 IdioVol_{i,t-1} \times LowCorrBK_{b,t-1} \\ &+ \alpha_4 AggVol_{i,t-1} \times LowCorrBK_{b,t-1} + \alpha_5 LowCorrBK_{b,t-1} \\ &+ \sum_j \gamma_j \mathbf{Firm}_{i,t-1} + \sum_k \theta_k \mathbf{Loan}_{f,t} + \sum_n \psi_n \mathbf{Bank}_{b,t-1} + \sum_t \delta_t T + \epsilon_{i,f,b,t} \end{aligned} \tag{4}$$

The results based on CAPM equity volatilities are presented in column 1 in Table 10. We find the idiosyncratic volatility is positively associated with loan spreads, suggesting that banks charge a risk premium for bearing the firm-specific default risk. On the contrary, the coefficient of aggregate risk is negative but insignificant. The interaction term between

[21] This analysis rests on an assumption that ex-ante banks make decisions on lending and pricing, given the existing loan portfolios and therefore interbank correlations. However, it is possible that a single loan can affect interbank correlations ex-post, depending on the aggregate exposure and relative size of the loan amount to bank assets.

idiosyncratic volatility and low correlation dummy is positive and significant. The interaction between aggregate volatility and low correlation dummy is negative and significant, suggesting that less correlated banks charge lower lending rates on aggregate risk relative to more correlated banks. Taken together, we find less correlated banks underprice aggregate risk more relative to more correlated banks.

To relax the restrictions of identical coefficients of the firm, loan and bank specific covariates for the two subgroups of lowly and highly correlated banks in the baseline regression, we divide the sample into two corresponding subsamples. The results of sample split are given in the columns 3 and 5. We find that aggregate risk is negatively and significantly priced by less correlated banks whereas insignificantly priced by more correlated banks. This indicates less correlated banks have stronger incentives to take aggregate risk of borrowers and therefore increase systemic risk. Doing the same exercise using Fama French equity volatilities, we have similar results in columns 2, 4 and 6. Overall, we find evidence that less correlated banks have stronger incentives to underprice aggregate risk and therefore take systemic risk, consistent with the "too-many-to-fail" story.

Since the test of "too-many-to-fail" based on banks' stock information may be biased by sample selection as the sample is restricted to publicly listed banks and excludes numerous unlisted small banks[22]. To correct for the sample bias, we also test the hypothesis that smaller banks are more aggressive in systemic risk-taking driven by "too-many-to-fail", as suggested by Acharya and Yozulmazer (2007). To test the impact of bank size on risk pricing, we construct a dummy variable *SmallBK* that equals one if the bank size is below the median value, and zero otherwise. The small bank dummy is then interacted with borrowers' equity volatilities. Overall, we run the following regression:

$$\begin{aligned} LoanSpread_{i,f,b,t} =& c + \alpha_1 IdioVol_{i,t-1} + \alpha_2 AggVol_{i,t-1} + \alpha_3 IdioVol_{i,t-1} \times SmallBK_{b,t-1} \\ &+ \alpha_4 AggVol_{i,t-1} \times SmallBK_{b,t-1} + \alpha_5 SmallBK_{b,t-1} \\ &+ \sum_j \gamma_j \mathbf{Firm}_{i,t-1} + \sum_k \theta_k \mathbf{Loan}_{f,t} + \sum_n \psi_n \mathbf{Bank}_{b,t-1} + \sum_t \delta_t T + \epsilon_{i,f,b,t} \end{aligned} \tag{5}$$

[22]These are relatively small lenders in the syndicated loan market, but not necessarily small banks in the absolute terms. The average size of the small banks is 15.9 billion USD.

We present the results in Table 11. In column 1, we find banks generally charge a higher spread for idiosyncratic risk. The coefficient for aggregate risk and the interaction between idiosyncratic risk and *SmallBK* are negative and insignificant. However, the interaction term between aggregate risk and *SmallBK* is negative and significant, suggesting that small banks underprice aggregate risk relative to big banks. In the end, the coefficient of *SmallBK* is positive but insignificant. Overall we find small banks underprice aggregate risk to idiosyncratic risk more relative to big banks do, indicating that small banks are more aggressive in taking systemic risk. For sensitivity analysis, we split the full sample into loans originated by small and big banks and report the results in columns 3 and 5. Our results continue to hold. The exercises based on Fama French equity volatilities in columns 1, 4 and 6 yield similar results. Taken together, we find small banks tend to underprice aggregate risk, which is different from the prediction of "too-big-to-fail" theory which asserts that large banks are likely to take risk to exploit the safety net.

7 Conclusion

This paper documents evidence of bank systemic risk-taking from loan pricing. We find loan spreads are positively associated with borrowers' idiosyncratic risk but negatively associated with aggregate risk. The lending rate discount for aggregate exposures reveals banks' preference for increased correlation and systemic risk. Relating this collective moral hazard to the "too-many-to-fail" guarantee in banking regulation, we show that no evidence of such systemic risk-taking could be found in the loans originated by non-bank lenders in absence of bailout expectation. In line with the "too-many-to-fail" theory in Acharya and Yorulmazer (2007), we find less correlated banks and smaller banks are more aggressive in systemic risk-taking as they underprice aggregate risk of the borrower more relative to more correlated banks and larger banks, respectively. The findings also suggest that the results are not driven by the "too-big-to-fail" guarantee.

Our findings have direct policy implications for macroprudential regulations. First, the fact that banks take advantage of the financial safety net and pass through regulatory subsidies to borrowers in the form of inappropriate pricing of risk may threat the stability of the entire banking sector. The prudential regulation should be designed to force banks to internalize the social costs incurred in systemic crises so that the incentive for systemic risk-taking is ameliorated. In particular, banking regulation should operate at the collective level to pay more attention to systemic risk on top of individual risk to cope with the collective moral hazard of systemic risk-taking (Acharya, 2009; Farhi and Tirole, 2009). For instance, systemic risk capital buffer requirement could be introduced as a policy instrument for macroprudential regulation. One recent example is that the Dutch central bank, De Nederlandsche Bank (DNB), intends to impose an additional capital buffer requirement on the four systemic banks in the Netherlands. In particular, this systemic buffer will be 3% of risk-weighted assets for ING Bank, Rabobank and ABN AMRO Bank, and 1% for SNS Bank. Second, much attention has been paid to systemically important financial institutions (SIFIs) which contribute substantially to systemic risk. However, in this paper we show that small and lowly correlated banks have been aggressive in taking systemic risk and need attention for regulation as well. Therefore, extra capital buffer requirement based on asset correlation, which is applied to every bank as capital requirement based on individual credit risk, could be a desirable policy instrument for macroprudential regulation.

Table 1: Summary Statistics

	No.	Mean	Std. Dev	Min	Median	Max
LoanSpread	11323	206.819	119.832	20.000	200.000	578.080
Borrower Equity Volatilities						
$TotalVol$	11323	0.575	0.303	0.171	0.500	1.709
$MarketVol$	11323	0.155	0.064	0.078	0.127	0.398
$IdioVol^{CAPM}$	11323	0.554	0.303	0.155	0.482	1.697
$AggVol^{CAPM}$	11323	0.116	0.101	-0.054	0.096	0.529
$IdioVol^{FF}$	11323	0.545	0.301	0.152	0.470	1.688
$AggVol^{FF}$	11321	0.154	0.103	0.021	0.129	0.585
$Beta^{CAPM}$	11323	0.758	0.564	-0.427	0.692	2.471
$Beta^{MKT}$	11323	0.965	0.624	-0.627	0.945	2.800
$Beta^{SMB}$	11323	0.833	0.787	-1.030	0.768	3.190
$Beta^{HML}$	11323	0.294	0.964	-2.593	0.301	3.131
Firm controls						
Log(Sales)	11323	5.611	1.729	1.635	5.563	9.847
LEVERAGE	11323	28.035	20.687	0.000	26.606	92.863
PROFMARGIN	11323	-0.871	22.044	-149.972	3.211	28.587
ROA	11323	12.193	11.015	-35.071	12.819	39.983
NWC	11323	21.107	20.804	-28.733	19.291	74.215
TANGIBLES	11323	69.036	36.672	5.675	66.819	177.554
MKTBOOK	11323	1.782	1.072	0.668	1.453	6.815
Loan controls						
Log(FacilitySize)	11323	3.805	1.767	-2.996	3.912	10.086
Maturity	11323	3.589	2.098	0.083	3.083	23.000
#Lenders	11323	6.050	7.716	1	3	113
#Facilities	11323	1.763	0.987	1	1	8
REVOLVER	11323	0.730	0.444	0	1	1
TERMLOAN	11323	0.244	0.429	0	0	1
SENIOR	11323	0.999	0.038	0	1	1
SECURED	11323	0.751	0.432	0	1	1
Corporate Purpose	11323	0.228	0.420	0	0	1
Debt Repayment	11323	0.247	0.431	0	0	1
Takeover	11323	0.166	0.372	0	0	1
Working Capital	11323	0.127	0.333	0	0	1
Other Purpose	11323	0.233	0.422	0	0	1
Bank controls						
SizeBK	11323	11.269	1.878	6.220	11.315	14.358
CapitalBK	11323	7.524	1.940	3.594	7.247	14.886
ROABK	11323	0.952	0.580	-1.693	1.037	2.215
ZscoreBK	11323	3.179	0.464	0.888	3.249	4.033
NPLBK	11323	0.936	1.022	0.000	0.556	4.912
LiquidityBK	11323	18.716	8.573	3.925	18.150	46.141
LoanGrowthBK	11323	20.476	38.342	-35.727	9.191	199.013
CostOfFundBK	11323	3.390	1.653	0.522	3.313	10.520
InterbankCorr	9321	0.735	0.161	-0.267	0.778	0.980

Table 2: Baseline regression CAPM

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. We use equity volatilities estimated from CAPM regressions. In column 1, we include equity volatilities only as explanatory variables. In column 2, we add firm specific variables as controls. In column 3, we further add loan specific variables as controls. In column 4, we include bank specific variables as well. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
$IdioVol^{CAPM}$	216.469***	129.264***	92.632***	91.788***
	(9.008)	(7.195)	(6.113)	(6.108)
$AggVol^{CAPM}$	-173.098***	-54.640***	-40.841***	-42.850***
	(20.374)	(15.442)	(14.337)	(14.273)
Log(Sales)		-20.732***	-6.497***	-6.010***
		(1.234)	(0.897)	(0.924)
LEVERAGE		0.984***	0.667***	0.676***
		(0.081)	(0.066)	(0.061)
PROFMARGIN		0.100	0.107	0.107
		(0.101)	(0.080)	(0.079)
ROA		-1.589***	-1.587***	-1.517***
		(0.235)	(0.167)	(0.142)
NWC		-0.249***	-0.251***	-0.257***
		(0.074)	(0.065)	(0.064)
TANGIBLES		-0.130***	-0.029	-0.036
		(0.041)	(0.032)	(0.032)
MKTBOOK		-0.060***	-0.010	-0.014
		(0.019)	(0.012)	(0.010)
Log(FacilitySize)			-9.513***	-8.491***
			(1.484)	(1.286)
Maturity			-4.167***	-4.042***
			(0.895)	(0.875)
#Lenders			-0.494***	-0.573***
			(0.167)	(0.164)
#Facilities			12.747***	13.083***
			(1.844)	(1.803)
REVOLVER			-37.931***	-37.681***
			(9.040)	(8.864)
TERMLOAN			-8.106	-7.624
			(10.546)	(10.367)
SENIOR			-190.679***	-193.901***
			(33.629)	(33.628)
SECURED			72.487***	72.047***
			(2.692)	(2.557)
SizeBK				-4.370***
				(1.261)
CapitalBK				-2.415***
				(0.916)
ROABK				1.173
				(3.162)

ZscoreBK				-2.274
				(3.695)
NPLBK				3.650*
				(2.136)
LiquidityBK				-0.265
				(0.229)
LoanGrowthBK				-0.073**
				(0.029)
CoftOfFundBK				-3.102
				(2.734)
Constant	171.445***	312.103***	421.445***	490.482***
	(12.735)	(13.282)	(36.335)	(40.460)
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	No	Yes	Yes	Yes
Loan Purpose Dummies	No	No	Yes	Yes
Observations	11,323	11,323	11,323	11,323
Adjusted R-squared	0.340	0.439	0.557	0.561

Table 3: Baseline regression Fama French

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. We use equity volatilities estimated from Fama French regressions. In column 1, we include equity volatilities only as explanatory variables. In column 2, we add firm specific variables as controls. In column 3, we further add loan specific variables as controls. In column 4, we include bank specific variables as well. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
$IdioVol^{FF}$	230.749***	134.597***	96.190***	95.415***
	(8.474)	(6.953)	(5.917)	(5.878)
$AggVol^{FF}$	-172.813***	-54.616***	-38.262**	-39.739**
	(20.038)	(16.470)	(16.248)	(16.329)
Log(Sales)		-20.628***	-6.495***	-6.018***
		(1.248)	(0.905)	(0.933)
LEVERAGE		0.981***	0.665***	0.674***
		(0.082)	(0.067)	(0.062)
PROFMARGIN		0.102	0.109	0.110
		(0.100)	(0.079)	(0.079)
ROA		-1.590***	-1.586***	-1.517***
		(0.232)	(0.166)	(0.141)
NWC		-0.240***	-0.246***	-0.252***
		(0.074)	(0.065)	(0.064)
TANGIBLES		-0.130***	-0.028	-0.036
		(0.041)	(0.033)	(0.032)
MKTBOOK		-0.059***	-0.010	-0.014
		(0.019)	(0.012)	(0.010)
Log(FacilitySize)			-9.440***	-8.417***
			(1.481)	(1.291)
Maturity			-4.185***	-4.061***
			(0.896)	(0.876)
#Lenders			-0.502***	-0.580***
			(0.167)	(0.164)
#Facilities			12.692***	13.028***
			(1.852)	(1.813)
REVOLVER			-37.656***	-37.416***
			(9.054)	(8.883)
TERMLOAN			-7.871	-7.395
			(10.547)	(10.374)
SENIOR			-190.935***	-194.210***
			(33.531)	(33.538)
SECURED			72.575***	72.134***
			(2.688)	(2.552)
SizeBK				-4.372***
				(1.259)
CapitalBK				-2.383***
				(0.911)
ROABK				1.239
				(3.144)

ZscoreBK				-2.220
				(3.692)
NPLBK				3.627*
				(2.137)
LiquidityBK				-0.269
				(0.228)
LoanGrowthBK				-0.074**
				(0.029)
CostOfFundBK				-3.072
				(2.745)
Constant	178.400***	314.396***	423.049***	491.838***
	(13.451)	(13.320)	(36.406)	(40.430)
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	No	Yes	Yes	Yes
Loan Purpose Dummies	No	No	Yes	Yes
Observations	11,321	11,321	11,321	11,321
Adjusted R-squared	0.342	0.440	0.557	0.561

Table 4: Robustness checks

In columns 1 and 2 we use equity betas as alternative proxies for aggregate exposure of the borrower. In columns 3 and 4 we use total volatility and share of aggregate volatility in total volatility. In columns 5 and 6 we use unlevered equity volatilities. The dependent variable in all specifications is all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$IdioVol^{CAPM}$	91.320***					
	(6.220)					
$Beta^{CAPM}$	-6.890***					
	(2.206)					
$IdioVol^{FF}$		91.226***				
		(6.140)				
$Beta^{MKT}$		-4.663**				
		(2.227)				
$TotalVol$			82.607***	82.352***		
			(6.396)	(6.430)		
$AggVol^{CAPM}/TotalVol$			-64.120***			
			(6.887)			
$AggVol^{FF}/TotalVol$				-72.637***		
				(8.811)		
Unlevered$IdioVol^{CAPM}$					70.517***	
					(8.274)	
Unlevered$AggVol^{CAPM}$					-88.809***	
					(13.533)	
Unlevered$IdioVol^{FF}$						77.391***
						(8.019)
Unlevered$AggVol^{FF}$						-85.602***
						(14.516)
Constant	486.443***	490.052***	499.646***	508.313***	522.334***	523.795***
	(40.229)	(40.339)	(40.588)	(40.419)	(39.942)	(39.711)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,323	11,323	11,323	11,321	11,323	11,321
R-squared	0.563	0.563	0.565	0.566	0.547	0.547

Table 5: Panel Regressions

In columns 1 and 2 we run panel regressions with firm fixed effects. In columns 3 and 4 we run panel regressions with bank fixed effects. The dependent variable in the all specifications is all-in-drawn spread. Standard errors are adjusted for clustering at the borrower level in the first two columns and at the lender level in the last two columns and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Firm FE		Bank FE	
	CAPM	Fama French	CAPM	Fama French
	(1)	(2)	(3)	(4)
$IdioVol^{CAPM}$	104.49***		93.14***	
	(8.78)		(7.09)	
$AggVol^{CAPM}$	-47.61**		-49.46***	
	(19.26)		(15.34)	
$IdioVol^{FF}$		106.92***		96.69***
		(9.09)		(6.60)
$AggVol^{FF}$		-35.89*		-42.86**
		(20.21)		(16.57)
Constant	450.41***	453.02***	421.12***	423.61***
	(63.45)	(63.50)	(65.56)	(66.00)
Firm controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No
Bank FE	No	No	Yes	Yes
Observations	11,323	11,321	11,323	11,321
Number of Firms	4,192	4,191		
Adjusted R-squared	0.332	0.332	0.494	0.494
Number of Banks			376	376

Table 6: Non-bank and Bank Lenders

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Non-bank (1)	Bank (2)	Non-bank (3)	Bank (4)
$IdioVol^{CAPM}$	55.222***	92.687***		
	(11.816)	(5.836)		
$AggVol^{CAPM}$	61.927*	-37.639***		
	(32.641)	(14.035)		
$IdioVol^{FF}$			51.767***	96.310***
			(12.844)	(5.650)
$AggVol^{FF}$			54.521*	-37.376**
			(32.490)	(15.893)
Constant	475.108***	490.106***	477.457***	491.353***
	(97.732)	(43.211)	(96.464)	(43.167)
Firm controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	1,796	12,233	1,793	12,231
Adjusted R-squared	0.341	0.541	0.341	0.541

Table 7: Prematch propensity score regression and postmatch diagnostic regression

In all specifications, we run Probit regressions. The dependent variable is a dummy for loans originated by non-bank lenders. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Dummy = 1 if the loan is originated by a non-bank lender; 0 if by a bank	
VARIABLES	Prematch	Postmatch
	(1)	(2)
$IdioVol^{CAPM}$	0.933***	-0.004
	(0.100)	(0.140)
$AggVol^{CAPM}$	-0.280	0.099
	(0.284)	(0.394)
LSALES	-0.032	0.029
	(0.030)	(0.043)
LEVERAGE	0.006***	0.000
	(0.001)	(0.002)
PROFMARGIN	0.003***	-0.000
	(0.001)	(0.001)
ROA	-0.018***	-0.000
	(0.004)	(0.006)
NWC	0.000	-0.001
	(0.002)	(0.002)
TANGIBLES	-0.000	-0.000
	(0.001)	(0.001)
MRTBOOK	-0.001***	-0.000
	(0.000)	(0.000)
Constant	-1.948***	-0.551
	(0.437)	(0.798)
Industry Dummies	Yes	Yes
Year Dummies	Yes	Yes
Observations	14,027	3,098
p-value of χ^2	0.000	0.998
Pseudo R2	0.129	0.007

Table 8: T-test for equality of means of borrowers' characteristics before and after matching

We compare the sample means of borrowers' characteristics before and after propensity score matching. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Unmatched sample			Matched sample		
Variables	Bank (1)	Nonbank (2)	Difference in means (3)	Bank (4)	Nonbank (5)	Difference in means (6)
$IdioVol^{CAPM}$	0.558	0.820	-0.262***	0.738	0.740	-0.002
$AggVol^{CAPM}$	0.116	0.111	0.004*	0.112	0.114	-0.002
$IdioVol^{FF}$	0.550	0.811	-0.262***	0.729	0.731	-0.002
$AggVol^{FF}$	0.155	0.168	-0.013***	0.165	0.164	0.001
Log(Sales)	5.576	5.101	0.475***	5.064	5.158	-0.094
LEVERAGE	28.159	33.894	-5.735***	31.805	32.611	-0.806
PROFMARGIN	-0.937	-9.762	8.825***	-8.848	-8.925	0.077
ROA	12.108	5.039	7.069***	6.341	6.328	0.013
NWC	21.037	19.003	2.034***	21.118	19.995	1.123
TANGIBLES	69.483	69.894	-0.411	68.629	69.151	-0.522
MKTBOOK	177.004	150.679	26.324***	157.242	155.430	1.812
Observations	12233	1796	14091	1549	1549	3098

Table 9: Non-bank and Bank Lenders: A propensity score matched sample

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Non-bank (1)	Bank (2)	Non-bank (3)	Bank (4)
$IdioVol^{CAPM}$	59.867***	94.836***		
	(16.145)	(12.272)		
$AggVol^{CAPM}$	69.523**	-72.335***		
	(35.179)	(22.117)		
$IdioVol^{FF}$			56.536***	100.220***
			(17.048)	(12.292)
$AggVol^{FF}$			62.066*	-66.838***
			(35.245)	(23.753)
Constant	638.863***	443.294***	636.691***	442.001***
	(95.358)	(56.447)	(94.545)	(55.935)
Firm controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	1,549	1,549	1,546	1,549
Adjusted R-squared	0.354	0.463	0.354	0.463

Table 10: Loan pricing and bank correlation

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Full Sample		Lowly Corr. Banks		Highly Corr. Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$IdioVol^{CAPM}$	88.374***		88.011***		102.139***	
	(9.153)		(8.592)		(11.185)	
$AggVol^{CAPM}$	-12.847		-63.378***		-21.722	
	(17.994)		(20.406)		(16.592)	
$IdioVol^{CAPM} \times LowCorrBK$	14.552*					
	(8.077)					
$AggVol^{CAPM} \times LowCorrBK$	-55.901**					
	(26.457)					
$IdioVol^{FF}$		90.164***		93.192***		105.670***
		(8.523)		(8.965)		(10.348)
$AggVol^{FF}$		-13.441		-63.119***		-25.506
		(19.839)		(23.248)		(17.938)
$IdioVol^{FF} \times LowCorrBK$		18.337**				
		(7.948)				
$AggVol^{FF} \times LowCorrBK$		-52.845**				
		(26.605)				
$LowCorrBK$	2.390	1.982				
	(5.728)	(5.704)				
Constant	495.228***	494.023***	478.592***	478.047***	442.636***	643.520***
	(51.926)	(51.687)	(116.247)	(115.420)	(65.557)	(59.925)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,321	9,319	4,658	4,657	4,663	4,662
Adjusted R-squared	0.572	0.572	0.592	0.592	0.564	0.564

Table 11: Loan pricing and bank size

In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spread. Standard errors are adjusted for clustering at the lender level and reported in parentheses below coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Full Sample		Small Banks		Large Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$IdioVol^{CAPM}$	106.381***		77.827***		113.753***	
	(7.175)		(6.790)		(9.287)	
$AggVol^{CAPM}$	-14.694		-68.752***		-15.842	
	(17.420)		(15.183)		(16.011)	
$IdioVol^{CAPM} \times SamllBK$	-22.469***					
	(7.944)					
$AggVol^{CAPM} \times SamllBK$	-57.116***					
	(21.621)					
$IdioVol^{FF}$		107.643***		84.200***		115.264***
		(6.843)		(7.205)		(8.834)
$AggVol^{FF}$		-10.540		-70.544***		-12.817
		(19.713)		(16.467)		(19.074)
$IdioVol^{FF} \times SamllBK$		-17.628**				
		(7.847)				
$AggVol^{FF} \times SamllBK$		-60.255***				
		(22.537)				
$SamllBK$	12.830*	12.621*				
	(7.428)	(7.394)				
Constant	506.037***	508.423***	468.019***	471.263***	465.321***	463.777***
	(48.045)	(48.045)	(57.554)	(57.743)	(77.704)	(77.367)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,323	11,321	5,655	5,654	5,668	5,667
Adjusted R-squared	0.562	0.562	0.517	0.517	0.581	0.581

References

Acharya, V. V. (2009): "A theory of systemic risk and design of prudential bank regulation," *Journal of Financial Stability*, 5(3), 224–255.

Acharya, V. V., H. Almeida, and M. Campello (2013): "Aggregate risk and the choice between cash and lines of credit," *The Journal of Finance*, 68(5), 2059–2116.

Acharya, V. V., and T. Yorulmazer (2007): "Too many to fail–An analysis of time-inconsistency in bank closure policies," *Journal of financial intermediation*, 16(1), 1–31.

Altunbas, Y., L. Gambacorta, and D. Marques-Ibanez (2010): "Bank risk and monetary policy," *Journal of Financial Stability*, 6(3), 121–129.

Bali, T. G., S. J. Brown, and M. O. Caglayan (2012): "Systematic risk and the cross section of hedge fund returns," *Journal of Financial Economics*, 106(1), 114–131.

Becker, B., and V. Ivashina (2014): "Cyclicality of credit supply: Firm level evidence," *Journal of Monetary Economics*, 62, 76–93.

Brandao-Marques, L., R. Correa, and H. Sapriza (2013): "International evidence on government support and risk taking in the banking sector," *FRB International Finance Discussion Paper 1086*.

Cai, J., A. Saunders, and S. Steffen (2011): "Syndication, interconnectedness, and systemic risk," Discussion paper, New York University.

Campbell, J. Y., and G. B. Taksler (2003): "Equity volatility and corporate bond yields," *The Journal of Finance*, 58(6), 2321–2350.

Carey, M., and G. Nini (2007): "Is the corporate loan market globally integrated? A pricing puzzle," *The Journal of Finance*, 62(6), 2969–3007.

Carey, M., M. Post, and S. A. Sharpe (1998): "Does corporate lending by banks and finance companies differ? Evidence on specialization in private debt contracting," *The Journal of Finance*, 53(3), 845–878.

Cordella, T., and E. L. Yeyati (2003): "Bank bailouts: moral hazard vs. value effect," *Journal of Financial Intermediation*, 12(4), 300–330.

Dam, L., and M. Koetter (2012): "Bank bailouts and moral hazard: Evidence from Germany," *Review of Financial Studies*, 25(8), 2343–2380.

Dennis, S. A., and D. J. Mullineaux (2000): "Syndicated loans," *Journal of financial intermediation*, 9(4), 404–426.

DeYoung, R., E. Y. Peng, and M. Yan (2013): "Executive compensation and business policy choices at US commercial banks," *Journal of Financial and Quantitative Analysis*, 48(01), 165–196.

Ericsson, J., K. Jacobs, and R. Oviedo (2009): "The determinants of credit default swap premia," *Journal of Financial and Quantitative Analysis*, 44(01), 109–132.

FAHLENBRACH, R., R. PRILMEIER, AND R. M. STULZ (2012): "This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis," *The Journal of Finance*, 67(6), 2139–2185.

FAMA, E. F., AND K. R. FRENCH (1993): "Common risk factors in the returns on stocks and bonds," *Journal of financial economics*, 33(1), 3–56.

FARHI, E., AND J. TIROLE (2009): "Collective moral hazard, maturity mismatch and systemic bailouts," Discussion paper, National Bureau of Economic Research.

FOCARELLI, D., A. F. POZZOLO, AND L. CASOLARO (2008): "The pricing effect of certification on syndicated loans," *Journal of Monetary Economics*, 55(2), 335–349.

GADANECZ, B., K. TSATSARONIS, AND Y. ALTUNBAS (2012): "Spoilt and lazy: the impact of state support on bank behaviour in the international loan market," *International Journal of Central Banking*, 8(4), 121–173.

GAUL, L., AND P. UYSAL (2013): "Can Equity Volatility Explain the Global Loan Pricing Puzzle?," *Review of Financial Studies*, 26(12), 3225–3265.

GROPP, R., C. GRUENDL, AND A. GUETTLER (2013): "The Impact of Public Guarantees on Bank Risk-Taking: Evidence from a Natural Experiment," *Review of Finance*, pp. 1–32.

GROPP, R., H. HAKENES, AND I. SCHNABEL (2011): "Competition, risk-shifting, and public bail-out policies," *Review of Financial Studies*, 24(6), 2084–2120.

HANSEN, L. P. (2012): "Challenges in identifying and measuring systemic risk," Discussion paper, National Bureau of Economic Research.

HERTZEL, M. G., AND M. S. OFFICER (2012): "Industry contagion in loan spreads," *Journal of Financial Economics*, 103(3), 493–506.

HOGGARTH, G., J. REIDHILL, AND P. J. SINCLAIR (2004): "On the resolution of banking crises: theory and evidence," Working paper, Bank of England.

HUBBARD, R. G., K. N. KUTTNER, AND D. N. PALIA (2002): "Are There Bank Effects in Borrowers' Costs of Funds? Evidence from a Matched Sample of Borrowers and Banks," *The Journal of Business*, 75(4), 559–581.

IVASHINA, V. (2009): "Asymmetric information effects on loan spreads," *Journal of Financial Economics*, 92(2), 300–319.

IVASHINA, V., AND Z. SUN (2011): "Institutional demand pressure and the cost of corporate loans," *Journal of Financial Economics*, 99(3), 500–522.

JAMES, C., AND A. KIZILASLAN (2014): "Asset Specificity, Industry-Driven Recovery Risk, and Loan Pricing," *Journal of Financial and Quantitative Analysis*, 49(03), 599–631.

KEELEY, M. C. (1990): "Deposit insurance, risk, and market power in banking," *American economic review*, 80(5), 1183–1200.

LAEVEN, L., AND R. LEVINE (2009): "Bank governance, regulation and risk taking," *Journal of Financial Economics*, 93(2), 259–275.

Lin, H., and D. Paravisini (2013): "The effect of financing constraints on risk," *Review of Finance*, 17(1), 229–259.

Merton, R. C. (1974): "On the pricing of corporate debt: The risk structure of interest rates," *The Journal of Finance*, 29(2), 449–470.

——— (1977): "An analytic derivation of the cost of deposit insurance and loan guarantees an application of modern option pricing theory," *Journal of Banking & Finance*, 1(1), 3–11.

Morgan, D. P. (2002): "Rating banks: Risk and uncertainty in an opaque industry," *American Economic Review*, 92, 874–888.

Santos, J. A. (2011): "Bank corporate loan pricing following the subprime crisis," *Review of Financial Studies*, 24(6), 1916–1943.

Santos, J. A., and A. Winton (2008): "Bank loans, bonds, and information monopolies across the business cycle," *The Journal of Finance*, 63(3), 1315–1359.

——— (2013): "Bank capital, borrower power, and loan rates," Discussion paper, NY Fed and University of Minnesota.

Strahan, P. E. (1999): "Borrower risk and the price and nonprice terms of bank loans," *FRB of New York Staff Report*, (90).

Sufi, A. (2007): "Information asymmetry and financing arrangements: Evidence from syndicated loans," *The Journal of Finance*, 62(2), 629–668.

Tucker, J. W. (2010): "Selection bias and econometric remedies in accounting and finance research," *Journal of Accounting Literature*, 29, 31–57.

Vives, X. (2011): "Competition policy in banking," *Oxford Review of Economic Policy*, 27(3), 479–497.

Zhang, B. Y., H. Zhou, and H. Zhu (2009): "Explaining credit default swap spreads with the equity volatility and jump risks of individual firms," *Review of Financial Studies*, 22(12), 5099–5131.

APPENDIX

Table A1: Data Descriptions and Sources

Variable	Description	Source
LoanSpread	The All-in-Drawn spread is an interest rate spread over LIBOR measured in basis points for each dollar drawn from the loan.	Dealscan
$IdioVol^{CAPM}$	Idiosyncratic volatility using one factor CAPM regressions. Defined as the standard deviation of the residual.	CRSP
$AggVol^{CAPM}$	Systematic volatility using one factor CAPM regressions. Defined as the product of beta and market volatility.	CRSP
$IdioVol^{FF}$	Idiosyncratic volatility from Fama French three-factor model. Defined as the standard deviation of the residual.	CRSP, WRDS
$AggVol^{FF}$	Systematic volatility from Fama French three-factor model. Defined as the total volatility that is attributable to Fama French factors and the factors cross-covariances.	CRSP, WRDS
$Beta^{CAPM}$	Equity beta estimated from the CAPM regression.	CRSP
$Beta^{MKT}$	Coefficient of the market factor estimated from the Fama French three-factor model.	CRSP
$TotalVol$	Total equity volatility, defined as the standard deviation of daily excess return one year before the facility start date.	CRSP
Unlevered$IdioVol^{CAPM}$	Idiosyncratic volatility using one factor CAPM regressions, unlevered by multiplying a ratio of equity/(debt+equity).	CRSP and Compustat
Unlevered$AggVol^{CAPM}$	Systematic volatility using one factor CAPM regressions, unlevered by multiplying a ratio of equity/(debt+equity).	CRSP and Compustat
Unlevered$IdioVol^{FF}$	Idiosyncratic volatility from Fama French three-factor model, unlevered by multiplying a ratio of equity/(debt+equity).	CRSP, WRDS and Compustat
Unlevered$AggVol^{FF}$	Systematic volatility from Fama French three-factor model, unlevered by multiplying a ratio of equity/(debt+equity).	CRSP, WRDS and Compustat
Log(Sales)	Logarithm of firm sales at close of the borrower.	Dealscan
LEVERAGE	Firm leverage defined as sum of long term and short term debts over total assets of the borrower.	Compustat
PROFMARGIN	Profit margin over sales of the borrower.	Compustat
ROA	Return on assets of the borrower.	Compustat
NWC	Net working capital over total assets of the borrower.	Compustat
TANGIBLE	Tangible assets over total assets of the borrower.	Compustat
MRTBOOK	Market to book ratio of the borrower.	Compustat
Log(FacilitySize)	Logarithm of facility amount in million USD.	Dealscan
MATURITY	Maturity of the facility in terms of years	Dealscan
#Lenders	Number of lenders in a tranche of a syndicated loan deal	Dealscan
#Facilities	Number of facilities (tranches) in a syndicated loan deal	Dealscan
REVOLVER	Dummy for lines of credit.	Dealscan

TERMLOAN	Dummy for term loans.	Dealscan
SENIOR	Dummy for senior loans.	Dealscan
SECURED	Dummy for loans with collateral.	Dealscan
Corporate Purpose	Loan purpose dummy indicates loans borrowed for corporate purpose.	Dealscan
Debt Repayment	Loan purpose dummy indicates loans borrowed for debt repayment.	Dealscan
Takeover	Loan purpose dummy indicates loans borrowed for takeover.	Dealscan
Working Capital	Loan purpose dummy indicates loans borrowed for working capital.	Dealscan
Other	Loan purpose dummy indicates loans borrowed for purposes other than the previous four.	Dealscan
SizeBK	Logarithm of bank total assets of the lender.	Call reports, FR Y-9C
SmallBK	Dummy for small banks.	Call reports, FR Y-9C
CapitalBK	Bank equity over total assets of the lender.	Call reports, FR Y-9C
NPLBK	Nonperforming loans over gross loans of the lender.	Call reports, FR Y-9C
ZscoreBK	Bank Z score, defined as sum of equity asset ratio and ROA divided by standard deviation of ROA. We use 8-quarter rolling window when calculating the standard deviation of ROA. We take log transformation as in Laeven and Levine (2009).	Call reports, FR Y-9C
ROABK	Return on assets of the lender.	Call reports, FR Y-9C
LiquidityBK	Liquid assets over total assets of the lender.	Call reports, FR Y-9C
CostOfFundBK	Cost of funds, defined as total interest expenses over total liabilities of the lender.	Call reports, FR Y-9C
LoanGrowthBK	Growth rates of gross loans of the lender.	Call reports, FR Y-9C
InterbankCorr	Interbank correlation, defined as the correlation between bank stock return and S&P 500 bank sector index.	CRSP, Datastream
LowCorrBK	Dummy for less correlated banks of which interbank correlation is below median value.	CRSP, Datastream

Table A2: Institutional types of non-bank and bank lenders

Lender Types	No. of facilities	No. of borrowers	No. of lenders
Panel A		Non-banks	
Corporation	31	22	17
Finance Company	1,704	930	161
Inst. Invest. Other	8	7	7
Insurance Company	13	8	4
Mutual Fund	1	1	1
Other	25	23	15
Specialty	1	1	1
Trust Company	7	6	3
Total	1,789	984	211
Panel B		Banks	
US Bank	12,130	4,402	567
Thrift or S&L	103	51	7
Total	12,233	4,453	574