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Abstract

Public guarantees extended during systemic crises can affect the relative pricing of risks in the financial system. Studying the market for syndicated loans, we find that banks require lower compensation for aggregate risk than for idiosyncratic risk, consistent with systemic risk-taking due to guarantees. The underpricing of aggregate risk is concentrated among banks that benefit more from exposure to public guarantees and disappears for non-bank lenders not protected by these guarantees. Estimates from loan spread regressions imply a sizeable guarantee that is passed onto borrowers, but also distortions in the economy's capital allocation.

JEL Classification: G21, G32

Keywords: public guarantees, too-many-to-fail, systemic risk-taking, loan pricing

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Systemic risk-taking at banks: Evidence from the pricing of syndicated loans[1]

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Abstract

Public guarantees extended during systemic crises can affect the relative pricing of risks in the financial system. Studying the market for syndicated loans, we find that banks require lower compensation for aggregate risk than for idiosyncratic risk, consistent with systemic risk-taking due to guarantees. The underpricing of aggregate risk is concentrated among banks that benefit more from exposure to public guarantees and disappears for non-bank lenders not protected by these guarantees. Estimates from loan spread regressions imply a sizeable guarantee that is passed onto borrowers, but also distortions in the economy's capital allocation.

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1. Introduction

Disruptions in the financial system can impose large costs on society. Faced with a situation of general weakness in the financial sector, governments, regulators and central banks undertake extensive measures to support institutions that are at risk of failing. Besides outright bail-outs, the long list of measures includes guarantees, the purchase of troubled assets and regulatory forbearance. Policy makers also tend to create a more favorable environment for financial institutions in such a situation, be it through blanket guarantees of liabilities, a reduction in interest rates, or direct support of asset prices. While principally less targeted in nature, these interventions particularly benefit institutions at the risk of failure as these have the greatest need for support.

Collectively, the measures amount to significant subsidies extended to troubled institutions during times of system-wide problems. At the extreme, they can be viewed as an implicit public guarantee not to let an institution fail when other institutions are also weak ("too-many-to fail"). A bank that is at risk of failing in times of good health of the banking system, by contrast, does not benefit from these guarantees. In the case of isolated problems, regulators have plenty of options available. They can seek private sector resolutions, such as mergers or liquidations, which do not require public support.[2]

While desirable from the ex-post viewpoint of safeguarding the stability of the financial system, these guarantees are likely to create distortions ex-ante. They lower the private cost of risk that tends to materialize across banks and hence can result in systemic risk-taking. Despite the magnitude of these subsidies,[3] there is, however, a paucity of evidence for distortions caused by them. Identifying such distortions has

2 Brown and Dinc (2011) show that regulators are more likely to be forbearing towards a failing bank when the banking system is weak. See also Hoggarth, Reidhill and Sinclair (2004) for a discussion of how regulatory interventions differ in individual and systemic crises.

3 Estimates of the total funds used for supporting the financial system during the crisis of 2007-2009 are in the range of 3 to 11 trillion USD (source: CCNMoney Bailout tracker).

proven challenging as there is no clear benchmark of how banks behave in the absence of too-many-to-fail guarantees.

In this paper we use loan pricing as a setting to study distortions from systemic guarantees. The idea is that public guarantees affect the relative prices of risk. In the absence of guarantees, a lender should require higher compensation for aggregate risk than for idiosyncratic risk, as the former is not diversifiable. A financial institution, however, may have a preference for aggregate risk as this makes its exposures more similar to those of other banks,[4] thus increasing its chances of benefitting from subsidies if it experiences difficulties. In the presence of systemic guarantees, financial institutions are hence expected to underprice aggregate risk relative to idiosyncratic risk.

We examine this question using a large sample of U.S. syndicated loans from the period 1988 to 2011. Studying individual loans has the advantage that one can control for a large number of factors that may impact pricing, such as borrower and lender characteristics, as well as the specifics of the lending contract. We decompose a borrower's equity volatility to obtain proxies for aggregate and idiosyncratic risk. Consistent with priors, we first find that banks charge higher loan spreads when borrowers have high idiosyncratic risk. The relationship between aggregate risk and loan spreads, however, is a negative one: banks are found to charge lower spreads for borrowers with higher aggregate risk. While the coefficient on aggregate risk itself is not economically significant, the difference to the coefficient on idiosyncratic risk is. Thus banks charge lower compensation for aggregate than for idiosyncratic risk.

An underpricing of aggregate risk, at odds with standard portfolio theory, supports the hypothesis of systemic risk-taking at banks. We provide further evidence

4 If a bank increases its aggregate exposure, it raises commonality with the other banks in the system, as these are also exposed to aggregate risk (thus aggregate risk leads to systemic risk). By contrast, taking on more idiosyncratic risk (for example, lending more in its region) will lower commonality as other banks tend to be exposed to different idiosyncratic exposures.

for systemic risk-taking exploiting variations in the institutional coverage of public guarantees. Non-bank lenders, such as finance companies, provide a natural control group as systemic guarantees are traditionally perceived as applying to banks only. We find that within this group of lenders, higher compensation is charged for aggregate risk than for idiosyncratic risk, the opposite of the pattern found for banks. The result continues to hold when we consider a matched sample of firms to account for the fact that non-bank lenders have a different clientele than traditional banks.

Systemic risk-taking incentives also differ between small and large banks. Large banks are already protected by their size ("too-big-to-fail"); the type of risks they take will not have a primary impact on their likelihood of benefitting from public guarantees. The incentives to increase exposure specifically to aggregate risk are hence limited. Consistent with this, we find that the underpricing of aggregate risk is much less pronounced at large banks; large banks also do not charge a negative spread for aggregate risk. Similar to bank size, the extent to which a bank is correlated with the rest of the banking system affects risk-taking incentives. A bank that is fairly correlated with other banks is already protected by too-many-to-fail and the incentives to underprice aggregate risk are low. Consistent with this we find that in the group of banks for which systemic risk-taking incentives are lower (correlated banks), the underpricing of aggregate risk is weaker and no negative spread is charged for aggregate risk. Likewise, banks that generally enjoy external support in the event of problems have lower additional benefits due to too-many-to fail. In accordance with this we find the underpricing of aggregate risk to be concentrated among banks with low expectations of outside support.

Our results support the idea that the pricing of loans reflects public guarantees. They do not seem to be consistent with alternative explanations, unrelated to public guarantees, of why aggregate risk may be underpriced. Using our estimates, we calculate a lower bound of the total implied subsidy to borrowers, amounting to 10 billion USD annually. The results have several noteworthy implications for policy. First,

regulators may consider expanding their macroprudential toolset to address systemic risk-taking arising from too-many-to-fail. Second, public guarantees to banks are partially passed on to borrowers, and thus may have positive side effects for the real economy. Third, public guarantees distort financing decisions in the economy by benefitting one group of borrowers at the expense of others (small and young firms with higher idiosyncratic risk are hence at a disadvantage to large firms with mainly aggregate exposures).

Recent theoretical work has shown that too-many-to-fail guarantees can create ex-ante distortions in different contexts. Acharya and Yorulmazer (2007) present a model where due to a time inconsistency problem, governments find it optimal ex-post to bailout banks when they are jointly failing. This is anticipated by banks ex-ante and causes them to invest in the same asset, with the effect being stronger at smaller banks. Farhi and Tirole (2012) show that a lenient monetary policy when it comes to refinancing banks provides banks with incentives to correlate. Their model also shows that distortions extend to the liability side: banks have an incentive to jointly engage in excessive maturity transformation in order to increase the expected benefit from public interventions. In Horvath and Wagner (2014), optimal macroprudential policies entail lowering capital requirements when the banking system experiences a negative shock, which in turn provides banks with incentives to source aggregate instead of idiosyncratic risk.

To our knowledge, our paper is the first to provide evidence for distortions arising from too-many-to-fail guarantees. There is, however, a significant literature on the impact of other public guarantees on bank risk-taking. This literature generally concludes that banks increase their risk-taking in the presence of government guarantees (Duchin and Sosyura (2012); Gropp, Hakenes and Schnabel (2010); Gropp, Gruendl and Guettler (2010); Hovakimian and Kane (2000); Boyd and Runkle (1993); Boyd and Gertler (1994); Demirguc-Kunt and Detragiache (2002)). Gropp, Grundl, and Guttler (2010) study the removal of public guarantees for German savings banks and

show that it led to lower risk-taking at such banks. Gropp, Hakenes and Schnabel (2010) show that public guarantees also impact unprotected banks because those banks adjust their risk-taking for competitive reasons. Mariathasan, Merrouche and Werger (2014) study banks that are perceived as more likely to benefit from government support, as reflected in their Fitch Support Rating. They find that these banks are more likely to be leveraged, weakly capitalized, and exposed to a severe liquidity mismatch. The evidence on the impact of public guarantees is nonetheless far from unambiguous. Some studies find that guarantees also reduce risk-taking (Kacperczyk and Schnabl 2011; Gropp and Vesala 2004; Cordella and Yeyati 2003), consistent with such guarantees increasing charter values.

While our analysis focuses on the asset side, there is a long-standing literature that analyses whether too-big-to-fail subsidies are reflected in the prices of banks' securities (Flannery and Sorescu (1996), Sironi (2003), Morgan and Stiroh (2005)). Acharya, Anginer and Warburton (2013) find that, while a positive relationship exists between risk and bond spreads for medium and small institutions, the risk-to-spread relationship is not present for the largest institutions. This is consistent with the bondholders of large financial institutions expecting that the government will shield them from the consequences of failure. Focusing on equity prices instead, O'Hara and Shaw (1990) find that positive wealth effects accrued to shareholders of banks that were named too-big-to-fail by the Comptroller in 1984. Recent literature has also suggested that a limit to the too-big-to-fail problem arises in the case of "too-big-to-save". Bertay, Demirgüç-Kunt and Huizinga (2013) provide evidence consistent with too-big-to-save in that systemically large banks are subject to greater market discipline, as evidenced by a higher sensitivity of their funding costs to risk proxies.

On the methodological side, our paper closely follows the literature on the pricing of syndicated loans (e.g., Dennis and Mullineaux (2000), Sufi (2007), Becker and Ivashina (2014)). This literature has identified a variety of factors that influence loan pricing. Some papers have also suggested using equity volatility as a market-based

measure of borrower risk (Gaul and Uysal (2013) and Santos and Winton (2013)), however, without differentiating among the source of risk (aggregate versus idiosyncratic). Related to systemic risk, Cai, Saunders and Steffen (2014) exploit the specific setting of the syndicated loan market to develop a novel measure of bank risk. Cai et al construct an index that captures the degree to which the portfolios of members of a loan syndicate overlap, and show that it is related to common measures of systemic risk.

Our benchmark for the pricing of risk is portfolio theory, which predicts that investors require a compensation for taking on aggregate risk. This prediction is confirmed in several asset markets (for example there is a large equity market premium). The slope of the security market line (that is, the unit compensation for aggregate risk) is also typically estimated to be positive (Black, Jensen, and Scholes (1972)), even though flatter than predicted by the CAPM.[5] Extending the insights from portfolio theory to banking, Acharya, Almeida and Campello (2013) argue that credit lines expose banks to non-diversifiable risk, and hence banks should require compensation for aggregate borrower risk. While portfolio theory also predicts that idiosyncratic risk is not priced at all, the evidence on this is mixed (e.g., Goyal and Santa-Clara (2003) show that idiosyncratic risk affects returns). However, when it comes to loans, compensation for idiosyncratic risk -- even if anticipated to be lower than for aggregate risk -- is unsurprising since diversification of loan portfolios is costly.[6]

The remainder of the paper is organized as follows. Section 2 sets out our hypotheses. Section 3 presents the data, methodology and summary statistics. Section 4 contains the empirical evidence. Section 5 concludes and draws policy conclusions.

5 An explanation for this comes from leverage constraints. For example, Frazzini and Pedersen (2014) argue that leverage constraints imply a preference for high-beta assets relatively to low-beta assets.

6 Malkiel and Xu (2006) present a model where some investors are prohibited from owning all securities, leading to a pricing of idiosyncratic risk.

2. Hypotheses

Under the standard assumptions of portfolio theory, investors do not require compensation for idiosyncratic risk as the latter is perfectly diversifiable. However, diversification cannot be taken as frictionless for loan portfolios, due to the presence of information asymmetries and other costs. Hence, lenders may also require compensation for idiosyncratic risk – but this compensation is expected to be lower than for aggregate risk[7] as partial diversification is possible. Besides a risk premium, lenders will also charge borrowers for the expected losses from defaults. These charges should only depend on the size of the expected losses, and if not, we would again expect them to be higher for aggregate risk.[8]

When lenders are banks, another important consideration arises: public guarantees. Such guarantees are primarily extended in systemic crises, that is, when many institutions experience problems at the same time. These interventions all amount to subsidies (explicit or implicit) that accrue to banks in the event of joint stress. Troubled banks are the primary beneficiaries of these subsidies; the value of any given subsidy is also larger to them because it is received at a time where they are in need of support. The consequence is that a bank should prefer experiencing a situation of weakness at a time of general weakness in the financial system, rather than being the only troubled institution.[9] This has implications for the pricing of aggregate risk. Exposing itself to more aggregate risk makes a bank more correlated to other banks and increases the likelihood of joint failure (systemic risk thus is the result of aggregate risk). By contrast, taking on idiosyncratic risk does not easily allow banks

7 We use the term aggregate risk instead of systematic risk when referring to loans since lenders create new assets when extending loans. There is hence no fixed market portfolio, and the concept of systematic risk does not readily apply. Note also that, while when there is a fixed supply of assets it is not possible for (a subset of) investors to become more correlated, this is possible when new assets can be created.

8 Lenders are expected to *implicitly* risk-averse because correlated defaults by borrowers may threaten the stability of their institution and require costly balance sheet adjustment. In this case, taking on aggregate default risk will impose higher costs on them.

9 Acharya and Yorulmazer (2007) provide a model to formalize the benefit from joint failures in the presence of too-many-to-fail policies.

to increase common exposures, as this would require a large number of banks to invest in the same (idiosyncratic) exposure. Public guarantees thus reduce the cost of aggregate risk for banks, relative to idiosyncratic risk. If this effect is sufficiently strong, it will outweigh the standard result of a higher aversion to aggregate risk.

Applying to the pricing of loans, this yields the following hypothesis:

Hypothesis 1: Banks require lower loan spreads for aggregate risk than for idiosyncratic risk due to the presence of public guarantees.

Banks are key for the functioning of the financial system. Public guarantees, which have the objective of safeguarding the stability of the financial system, thus tend to focus on banks. Non-bank lenders, such as finance companies and corporations, are less likely to benefit from such guarantees.[10] Systemic risk-taking incentives are thus largely absent and the standard predictions of portfolio theories with limited diversification apply. We thus hypothesize that

Hypothesis 2: Non-bank lenders require higher loan spreads for aggregate risk than for idiosyncratic risk as they are not protected by public guarantees.

The prediction contained in Hypothesis 1 is also consistent with "myopic" herding by managers. Managers may have a tendency to follow their peers for behavioral reasons, and this may result in them displaying a preference for correlated risks. Herding may also be (individually) rational in the presence of career concerns (Scharfstein and Stein (1990)), as managers are less likely to be dismissed when they underperform jointly with their peers. However, if this were the reason behind the aggregate risk-taking, we would expect non-bank lenders to display herding as well,

[10] While during the subprime crisis also a few non-banks were bailed out, *expectations* of bailouts are thought to arise for banks mainly. For instance, Labonte (2015) writes that "because some non-bank financial firms did not receive analogous government protection before the crisis, there was not seen to be a moral hazard problem that justified regulating them for safety and soundness".

inconsistent with Hypothesis 2. In addition, systemic risk-taking due to public guarantees predicts that it predominantly arises for banks that are not yet protected by public guarantees. Large banks, by contrast, are already covered by the too-big-to fail guarantee. They are considered systemic by regulators regardless of how correlated they are with other banks. Thus, if public guarantees are behind the incentives to take on aggregate risk, the effects should be stronger at small banks, as formally shown in Acharya and Yorulmazer (2007).

Hypothesis 3: Small banks require a lower loan spread for aggregate risk than large banks.

For similar reasons, banks that are already correlated with other banks benefit less from taking on aggregate risk. These banks are already protected due to the "too-many-to-fail" guarantee. We hence also hypothesize that

Hypothesis 4: Less correlated banks require a lower loan spread for aggregate risk than more correlated banks.

The idea behind Hypotheses 3 and 4 is that banks that are already protected in the event of failures have less incentives to increase their likelihood of benefitting from "too-many-to-fail". While the hypotheses relate to protection arising from public guarantees, the argument applies to expectations of external support generally (that is, support from public authorities or from private investors in the event of distress). We can thus also formulate the following hypothesis:

Hypothesis 5: Banks with a low likelihood of external support in the event of distress require a lower loan spread for aggregate risk than banks with a high likelihood of external support.

3. Data and Methodology

3.1 Data

We use the syndicated loan market as a field for testing our hypotheses. Syndicated loans are an important source of finance for large U.S. corporations (Sufi (2007); Becker and Ivashina (2014)) and represent a substantial fraction of bank loan portfolios (Ivashina (2009)). Studying syndicated loans has the unique advantage that both banks and non-banks are active in this market. We can thus exploit non-banks as a natural control group for which lending should not be governed by expectations of public guarantees. Another advantage is that, compared to ordinary loans, relationship arguments play less of a role.

We consider syndicated loans contained in the Dealscan database and restrict the universe to publicly listed U.S. firms borrowing from U.S. banks during the period between 1988 and 2011. We exclude loans extended to US borrowers in financial industries (SIC codes 6000 to 6400, Finance and Insurance). Syndicated loans are usually structured in a number of facilities, also called tranches. We treat multiple facilities in a deal as different loans because spreads, identity of lenders and other contractual features often vary. An individual observation in our analysis is thus a loan facility extended by a syndicate to a borrower.

We merge the facility-level data with Compustat in order to obtain annual accounting information of the borrowers.[11] In addition, we collect daily stock return data from CRSP over the 12 months prior to the facility activation date. We drop borrowers with less than 100 trading days available in the event window. Moreover, we collect Fama-French Factors from Wharton Research Data Services (WRDS).

11 We are grateful to Sudheer Chava and Michael Roberts for providing the link between Dealscan and Compustat (see Chava and Roberts (2008))

Syndicates consist of one or more lead arrangers and other participants. We restrict our sample to loans originated by a single lead arranger. Lead arrangers collect information and monitor the borrower on behalf of the syndicate (Dennis and Mullineaux (2000); Sufi (2007); Santos and Winton (2008)). In addition, they set lending rates and the non-pricing loan terms. By contrast, the participants play a passive role in the syndicate. Hence, it is reasonable to assume that a sole lead arranger plays a role similar to a lender in a bilateral loan.

We manually match lead banks in Dealscan with commercial banks in the 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. We deal with mergers and acquisitions by matching the loan of the acquired lender to the accounting information of its acquirer. In addition to accounting data, we collect daily bank stock returns from CRSP for the 12 months preceding the loan origination. The price data is matched with the accounting information (from the Call Reports and FY Y9C) using the CRSP-FRB link from the FED New York. For this, accounting information of unlisted commercial banks is matched with stock return data of the parent companies, following Lin and Paravisini (2013). We also collect data on the S&P 500 banking sector index from Datastream dating back to the last quarter of 1989. Our measure for external support (Hypothesis 5) is a bank's support rating from Fitch (the support rating is the agency's assessment on the likelihood of extraordinary support from shareholders or national authorities in case of need).

3.2 Loan pricing model

We employ the following loan pricing model:

$$LoanSpread_{f,i,b,t} = c + \alpha_1 IdioRisk_{i,t-1} + \alpha_2 AggRisk_{i,t-1} +$$

$$\sum_j \gamma_j \boldsymbol{Firm}_{i,j,t-1} + \sum_k \theta_k \boldsymbol{Loan}_{f,k,t} + \sum_n \varphi_n \boldsymbol{Bank}_{b,n,t-1} + \sum_t \delta_t T_t + \epsilon_{f,i,b,t}$$

where *f*, *i*, *b* and *t* denote facility, firm, bank and year, respectively. The dependent variable, *LoanSpread*, is the all-in-drawn spread (over LIBOR) measured in basis points. The all-in-drawn-spread is a measure of the overall costs of the loan, accounting for both one time and recurring fees. *IdioRisk* and *AggRisk* denote the idiosyncratic and aggregate risk of the firm, respectively (to be explained in more detail below). In most regressions we include firm specific variables ($\boldsymbol{Firm}_i$), loan specific variables ($\boldsymbol{Loan}_f$), bank specific variables ($\boldsymbol{Bank}_b$) and year dummies T_t. ϵ is the error term.

We proxy borrower risk using equity volatilities as in Gaul and Uysal (2013) and Santos and Winton (2013). The idea is that one can view the lender as the owner of a safe bond who has issued a put option to equity of the firm (Merton (1974)). The put option reflects the limited liability of equity holders in the event of default. Increased equity volatility raises the value of a put option, as a firm with more volatile equity is more likely to reach the bound condition for default. Equity volatility is thus a proxy for the likelihood of firm default.[12]

To arrive at a measure of idiosyncratic and aggregate risk, we decompose borrowers' equity volatility into an idiosyncratic and an aggregate risk component. For this we run a standard CAPM regression as follows:

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

where $r_{i,d}$, $r_{m,d}$ and r_d^f represent (daily) individual stock 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 idiosyncratic risk as the standard deviation of the residual, $IdioRisk = SD(\epsilon)$.

[12] Consistent with this, equity volatility has been shown to explain credit spreads. In a seminal paper Campbell and Taksler (2003) provide evidence that equity volatility has substantial explanatory power for corporate bond yields. Zhang, Zhou and Zhu (2009) and Ericsson, Jacobs and Oviedo (2009) apply the same logic to credit default swap (CDS) pricing and find equity volatility is an important determinant of CDS spreads.

Aggregate risk is defined as the product of beta and market volatility, $AggRisk = \beta \times MarketVol$, where $MarketVol$ is the standard deviation of the market excess return ($SD(r_m - r^f)$). Note that aggregate risk (or, more precisely, exposure to the aggregate factor) is negative when a firm has a beta of less than zero (and is thus different from aggregate volatility, which is always positive). In such a case, extending a loan to a firm will reduce the aggregate risk of the lender, the opposite of what happens when lending to positive-beta firms.[13]

As an alternative, we also consider a decomposition based on the Fama French three-factor model (Fama and French (1993)). For this we adopt the following regression:

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

where the market factor MKT_d is the value-weighted 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. Idiosyncratic risk is measured as before by the residual $IdioRisk^{FF} = SD(\epsilon)$ and aggregate risk is given by $AggRisk^{FF} = \beta^{MKT} \times MarketVol$ (we do not include the other two factors in aggregate risk as net exposure to them is zero). We annualize all risk measures by using a multiplier of $\sqrt{252}$.

While these two decompositions provide measures of aggregate *market* risk, we also create a measure of a firm's exposure to the *banking* sector risk. For this we replace in the CAPM decomposition the market return with the S&P500 banking index. The resulting aggregate risk measure ($AggRisk^{Bank}$) can be thought of as how much

[13] Note that our estimation is possibly prone to a measurement error problem as the estimated equity volatility will not perfectly measure default risk. Almeida, Campello and Galvao (2010) argue that lags of estimated variables are useful instruments to address this problem. In our case, essentially we are using lagged equity volatility (estimated from prior stock return data) to proxy for current default risk, which is also the approach adopted by Acharya, Almeida and Campello (2013).

a firm is exposed to “systemic” risk. Similar to the argument for aggregate risk, banks may also have an incentive to source loans to firms that are correlated with other banks -- as this increases the likelihood of joint distress.

We include a number of firm level controls that may affect the lending rates. *Log(Sales)* is the logarithm of the firm's sales at the time of the deal (in millions of dollars). Since large firms are more transparent, we expect them to have lower spreads. *Leverage* is the ratio of total debt to total assets. Leveraged firms are more likely to default and hence are expected to be charged a higher lending rate. We also include *ProfMargin* (the ratio of profits to sales) and *ROA* (the return on assets) to measure profitability. As more profitable firms are safer, they should be charged a lower spread. We also include two controls for a firm’s loss given default (LGD).[14] *NWC* is the 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, *Tangibles* measures the fraction of tangible assets on the balance sheet. Borrowers with more tangible assets are more informationally transparent (Morgan (2002)) and have higher values in the event of default. We hence expect them to exhibit lower spreads. We also control for the Market-to-Book ratio, *MktBook*, as a proxy of Tobin's q. 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 one-digit SIC codes, as loss given default (LGD) is strongly correlated with industry characteristics (Hertzel and Officer (2012); James and Kizilaslan (2014)).

We also consider the non-price terms of deals for our analysis. Their coefficients have to be interpreted with caution as they are jointly determined with loan spreads and are therefore endogenous. First, we include *Log(FacilitySize*), the log of the facility amount. Large loans are associated with greater credit risk and lower liquidity, but

[14] We do not include the credit ratings of the borrower since we use equity risk as a proxy for default risk.

could also be demanded by larger firms which are more resilient. The relationship between loan size and loan pricing is hence ambiguous. We also include *Maturity*, the maturity of the facility measured in years. The effect of maturity on loan spreads is also ambiguous, for similar reasons as loan size. 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*).[15] 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 reduce the lenders' exposure in the event of borrower default and therefore lower lending rates, however, they are also more likely to be used for risky borrowers. The relationship between seniority, collateral and loan pricing is hence an empirical question. Last, we create five dummies to control for the loan purpose (Corporate Purposes (*CorpPurposes*), Debt Repayment (*Repayment*), Takeover (*Takeover*), Working Capital (*WorkCapital*) and Other (*OtherPurposes*)).

Next, lenders' characteristics may also affect the pricing of loans and have been included in recent studies (e.g., Hubbard, Kuttner and Palia (2002); Santos (2011); Santos and Winton (2013)). First, we include *SizeBk* as the logarithm of a bank's total assets in millions of dollars. Large banks usually have diversified portfolios and more advanced risk management, therefore we expect them to be able to charge lower lending rates. Next, we control for *CapitalBk*, the ratio of capital to total assets. Well capitalized banks are more likely to have additional risk capacity and therefore are expected to charge a lower spread. In addition, we use *NPLBk*, the ratio of nonperforming loans to total assets, as a measure of bank credit risk. Risky banks may require additional compensation for taking on further risk. Hence, we expect banks with more nonperforming loans to charge a higher spread. We also use *ZscoreBk* as a

[15] In particular, a loan is classified as a revolver if the loan type is expressed in Dealscan as "364-Day Facility", "Revolver/Line < 1 Yr. '', "Revolver/Line >= 1 Yr. '', "Revolver/Term Loan'', "Demand Loan'', or "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'', or "Delay Draw Term Loan''.

measure of bank insolvency risk. We calculate the Z-score following Laeven and Levine (2009) but using an eight-quarter rolling window. Moreover, we include the return on assets of the bank, *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*, which is the ratio of cash and liquid securities to total assets. Besides, we use the growth rate of loans (*LoanGrowthBk*) to measure the investment opportunities of the lender. Finally, we include *CostofFundBk*, which is the total interest expenses over total liabilities, to measure funding costs. In addition, we consider *InterbankCorr*, which is the correlation of a bank's daily excess return with the S&P 500 banking sector over the twelve months prior to loan origination. Last, we include *Support,* which is the support rating of the bank (this rating is on a five-point scale, with "1" representing an extremely high probability of support, and "5" indicating that support cannot be relied on).

We match borrower and lender accounting information from the fiscal year ending in the calendar year *t-1* to loans made in calendar year *t*. To mitigate the influence of outliers, we winsorize loan spreads, firm and bank specific variables and the two risk measures at 1 and 99 percentile levels. We also include year dummies to capture time trends throughout the analysis since the business cycle may affect loan contracts (Santos (2011)).[16]

3.3 Summary Statistics

The final sample consists of 11,317 facilities taken out by 4,190 publicly listed U.S. firms and financed by 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. Average idiosyncratic risk based on the CAPM is 0.55, while the average aggregate risk is 0.12. Idiosyncratic and aggregate risk estimated from the Fama French three-factor models resemble the ones estimated for the CAPM

[16] A detailed description of the variables is contained in the appendix.

model.

Among the firm controls, the average log of firm assets is 5.61 and the mean of borrowers' leverage is 28.035%. The profit margin is highly skewed, with a mean of -0.87% and a median of 3.21%. The average return on assets is 12.19. The mean of net working capital to total assets and tangible assets to total assets are 21.12% and 69.01%, respectively. The average Market-to-Book ratio is 1.78.

Turning to the loan characteristics, the average logarithm of the facility amount is 3.80. Syndicated loans in the sample have a mean maturity of 3.59 years. In addition, on average each syndicate has six lenders and is structured into 1.75 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 and about 75% of loans are secured by collateral.

The bank characteristics are all expressed in ratios, except for bank size and Z-score which are in logarithmic terms. Banks are much larger than the average firm in the sample, the mean of the log of their assets being 11.27. The average capitalization ratio (equity to asset) is 7.52% and the return on assets is 0.95%. The mean of the Z-score is 3.18. Liquid assets account for 18.72% of total assets and the average share of nonperforming loans to gross loans is 0.94%. The median of the loan growth rate is 9.19%; the average is relatively high at 20.48%. The average bank has a cost of funds at 3.39%. As not all banks are listed, we have information of interbank correlation for approximately 9321 facilities; the average interbank correlation is 0.73. The data on support ratings is even sparser. It is available for 3,452 loans and the average support rating is 3.42.

4. The pricing of risks in the syndicated loan market

4.1 Pricing by banks

Table 2 contains the results from the baseline pricing regression where the dependent variable is the all-in-drawn spread. All specifications are based on OLS regressions that pool all facilities; standard errors are clustered at the bank-level.

Column (1) reports results from a regression of loan spreads on the two risk measures and year dummies only. The coefficient on idiosyncratic risk is 216 and significant at the 1% level, indicating that banks require compensation for taking on idiosyncratic exposures. As discussed, this is in line with expectations since there are frictions to diversifying credit risk and hence CAPM theory does not apply. The coefficient on aggregate risk is -173 and is also significant at the 1% level. Thus, banks charge lower compensation for aggregate risk than for idiosyncratic risk: the spread difference between one unit of aggregate and idiosyncratic risk is 389 (-173-216) and is significant at the 1% level. This provides strong support for Hypothesis 1, in particular since in the absence of systemic risk-shifting, we would expect higher compensation for aggregate exposures than for idiosyncratic ones. Another interesting finding is that the coefficient on aggregate risk is a negative one, that is, banks pay for being exposed to aggregate risk. It can be explained by banks perceiving large subsidies from greater exposure to the aggregate (alternatively, it may reflect managerial herding, and issue to which we return later).

In column (2), we include firm controls and industry dummies. The coefficients on idiosyncratic and aggregate risk decrease in absolute terms, but remain significant. The compensation for idiosyncratic risk falls to 129, while the compensation for aggregate risk is -54. The firm characteristics have the expected signs and are mostly significant. In particular, we find that larger firms, firms with higher profitability, and less leveraged firms pay lower loan spreads. The proxies for loss given default (net working capital and tangible assets) also have the 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 the facility-specific variables. Hypothesis 1 continues to be supported, as aggregate risk has lower compensation than idiosyncratic risk. Moreover, we find that larger loans and loans with longer maturity are charged at a higher rate. The two proxies of the syndicate structure have opposite effects. Loans with more lenders are associated with lower spreads, whereas loans with more facilities are more expensive. We also find that lines of credit are generally cheaper, which is consistent with prior findings in the literature. A loan is also cheaper if it is senior, which may reflect that such loans have lower losses in a default. Furthermore, a secured loan is charged a higher spread than a loan without collateral. This may reflect the endogeneity of collateral as risky borrowers are more likely to be required to post collateral.

In column (4), we add the bank level controls. The main results continue to hold. Specifically, the coefficients on idiosyncratic and aggregate risk are 92 and -43, implying a difference in risk compensation of 135. The difference is statistically significant at the 1% level and is economically meaningful. Suppose that a bank were to price aggregate risk at least as high as idiosyncratic risk (as suggested by standard theory). Then the risk compensation would rise from -43 to 92. Given a sample mean for aggregate risk of 0.12, this would imply a loan spread that is on average 16 bps higher, about 8% of the mean loan spread. Note that the compensation for aggregate exposure itself is not economically meaningful: a one standard deviation (0.10) increase in the aggregate risk lowers the loan spread by 4 bps (=0.10 x -42.85). This suggests that the perceived public guarantees roughly offset the economic cost of taking on aggregate risk. Turning to the bank controls, we find that larger banks, better-capitalized banks, banks with higher costs of funding and banks with higher loan growth rates charge lower spreads while more risky banks charge relatively higher spreads.

In what follows, we take the regression with the full set of controls (column (4) of Table 3) to be our benchmark regression. Table 4 next considers the robustness of the result (for brevity, we do not report estimated coefficients of firm, loan and bank-level

control variables). Column (1) reports a regression where we use a different decomposition of aggregate and idiosyncratic risk, based on the Fama French three-factor model. As the Fama French model has more factors, it leads to a narrower concept of idiosyncratic risk. However, the coefficient on idiosyncratic risk is similar to the baseline model. The coefficient on aggregate risk is now insignificant – but the difference in the risk compensation between aggregate and idiosyncratic risk is 114 and significant as in the baseline model. In column (2) we report results based on a decomposition of risk using the banking index instead of the market index. The results are similar to the baseline model – though the coefficient on aggregate risk is now more negative.

In our analysis equity volatility measures credit risk by serving as a simple proxy for (unobserved) firm asset volatility. However, the contingent claims model suggests that equity volatility is a more complex function of both asset volatility and leverage. If 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)). We hence employ an alternative measure of credit risk based on a deleveraged equity volatility. For this, we follow James and Kizilaslan (2014) and multiply equity risk by the term 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. Column (3) reports the result using the unlevered measures. The coefficients decrease for both idiosyncratic and aggregate risk; the relative underpricing of aggregate risk remains increases somewhat (-159.2=-88.7-70.5).

We next consider an alternative way to test Hypothesis 1. While in the prior analysis we compared the coefficient on aggregate to that of idiosyncratic risk, we now include the ratio of aggregate to total risk (*AggRiskShare*) as a single variable of interest. A lower compensation for aggregate than for idiosyncratic exposures implies that lower loan spreads are charged when a larger proportion of total risk comes in the

form of aggregate exposure. Controlling separately for total risk (measured by the equity volatility), Hypothesis 1 thus suggests a negative coefficient on the risk ratio. The results in column (4) show that the ratio obtains a negative and significant coefficient of -64.1, thus confirming Hypothesis 1. The coefficient on total risk is positive (82.6) and significant, showing that banks overall charge higher spreads when taking on more risk.

A lower coefficient on aggregate risk may also arise when banks have a very high existing exposure to a specific idiosyncratic risk. To illustrate, suppose that a bank operates exclusively within a single region, and that for its loan portfolio the total idiosyncratic (regional) risk is higher than the aggregate risk. It may then require a higher marginal compensation for taking on more idiosyncratic risk from its region. This setting is less plausible for our sample of syndicated loans; these loans are given by relatively large banks to predominantly large firms and are less likely to reflect regional specialization. Nonetheless, in column (5) we report results from a regression where we only include interstate loans, that is, loans extended by a bank to a firm from a different state. In this case, the idiosyncratic risk of the firm should have a diversifying impact on any existing regional risk concentration the bank may have. The results show a coefficient on idiosyncratic risk (97) slightly higher than in the benchmark, inconsistent with the idea that the benchmark results are driven by non-diversifiable idiosyncratic risk. The coefficient on aggregate risk is now insignificant, however, it is still significantly lower than that on idiosyncratic risk.

The baseline specification may be prone to an omitted variable bias if unobserved firm characteristics drive both firm risk and loan spreads. For example, firms with higher aggregate risk may be more transparent and banks may charge lower spreads for transparent firms. Or, firms with more aggregate risk may have more bargaining power (unrelated to firm size) and hence be able to obtain lower spreads. To take care of unobservable (time-invariant) firm heterogeneity, we estimate a firm fixed effects model. In particular, 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. The identification now comes from variations in risk and loan spreads for the same firm across time. The results in column (6) of Table 5 show results very similar to the baseline model. The coefficient on idiosyncratic risk is now 104.25 and the coefficient on aggregate risk is -47.61. The latter coefficient is only significant at the 5% level; the weaker significance can be attributed to the fact that there are not many different observations at the firm-level (a firm borrows on average 2.7 facilities in the sample).

Similarly, an omitted variable bias may arise from unobserved lender characteristics that affect lending 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 business model or risk culture may affect their pricing of loans (although it is less obvious how they can explain a differential pricing of idiosyncratic and aggregate risk). To take account of unobserved time-invariant bank characteristics, we estimate a bank fixed effects model. Column (7) shows that the results are again very similar to the baseline model, the coefficients on idiosyncratic and aggregate risk being 93.03 and -49.55, respectively.

Remaining endogeneity concerns are limited to unobserved time-varying firm or bank effects. For example, there may be a firm characteristic that varies over time and which is related to both the firm’s risk and its loan spreads. Since our main hypothesis relies on comparing the coefficients for aggregate and idiosyncratic risk, such a characteristic would also need to affect idiosyncratic and aggregate risk differently to create a bias. To address the residual endogeneity concerns, we adopt an instrumental variable approach. We first focus on the regression with the share of aggregate to total risk, as we then only have one variable of interest to worry about. As an instrument we use a measure of the number of a firm’s business lines and its extent of geographic diversification. The idea is that a more diversified business (in terms of business lines

or geographic reach) will have less idiosyncratic risk, and hence display a high ratio of aggregate risk. We collect data from Compustat Historical Segments on a firm's sales in various business lines and geographic areas. From this we create for either variable a diversification index, defined as 1 minus the Herfindahl-Hirschman-index (HHI) (Jacquemin and Berry (1979)). Column (1) in Table 4 reports the first stage regression. Both diversification indices are significant and positively associated with the aggregate risk ratio. The results also pass the F-test. In column (2), we find the instrumented share of aggregate risk in the total risk to be negatively associated with loan spreads. The coefficient is larger in absolute values compared to the uninstrumented regression (-136.76 versus -64.14), indicating that accounting for endogeneity strengthens the results. It should be taken into account though that at the same time the significance level is much weaker. Both the underidentification test and the Hansen J-test suggest that the two-stage least square results are valid. Column (3) and (4) repeat the exercise, instrumenting this time aggregate risk instead of the risk share. The first stage is weaker in that now only geographic diversification is significantly related to aggregate risk. A reduced significance is to be expected since diversification reduces idiosyncratic risk, but does not necessarily increase aggregate risk.[17] The second stage obtains a negative coefficient of -298.79 for the instrumented variable, which again is more negative than the corresponding coefficient in the baseline model (-172.94).

We carry out additional robustness results (unreported). First, the main result holds when standard errors are clustered at the firm-bank pair level or the year-bank pair level. Second, the analysis is robust to the exclusion of credit lines from the analysis (the relative underpricing is then 147, as opposed to 134 for the full sample). Third, we exclude firms with negative beta (and hence negative aggregate risk exposure), with little change to the baseline results. Fourth, when we exclude leverage from the firm-controls (which may be correlated with credit risk) the results are again very similar to those of the baseline model. Fifth, regression on the pre-crisis period (1988-

[17] Banks may respond to diversification though by taking on new risks, hence driving up aggregate risk (Wagner (2008)).

2006) yields similar results. Last, our results hold when using raw data without winsorizing.

Taken together, this section has provided evidence that loan spreads are positively associated with idiosyncratic risk but negatively associated with the aggregate risk of the borrower. This provides support for our main hypothesis, which states that lenders may underprice aggregate risk because of public guarantees.

4.2 Pricing by different groups of lenders

Non-bank lenders

The previous section provided evidence consistent with systemic risk-taking by banks. When banks benefit from public guarantees, they have an incentive to take on aggregate risk, resulting in an underpricing of this risk relative to idiosyncratic risk. However, a more favorable pricing of aggregate risk may in principle also arise unrelated to public guarantees, for example due to managerial herding. In this section we compare the pricing of risk by lenders that are not equally covered by several types of guarantees. If the pricing pattern among these lenders varies consistent with guarantees, this provides further support for systemic risk shifting at banks.

We first compare the pricing of banks to that of other lenders. An interesting feature of the syndicated loan market is that a significant portion of loans are issued by non-bank financial institutions and corporates.[18] Non-banks are expected to benefit significantly less from public guarantees and we hence expect their pricing not to be governed by systemic risk-taking incentives. We thus consider them as an important control group. We exclude investment banks and mortgage companies from the universe of non-bank lenders, as these institutions are partly covered by public

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

guarantees. This leaves us with a sample of 1,789 facilities originated by non-bank institutional investors. The sample composition is summarized in Table 14, showing that the vast majority of lenders in this group are finance companies. As a comparison group with strong bailout expectations, we consider the pool of loans issued by commercial banks, bank holding companies, thrifts, savings and loan associations (S&Ls).[19]

Table 5 reports the loan pricing results for non-bank lenders and bank lenders. In the regressions, we only control for borrower, loan-specific variables and year dummies since accounting information for non-bank lenders is less readily available than for banks. Column (1) confirms our prior results in that bank lenders underprice aggregate risk relative to idiosyncratic risk.[20] Column (2) shows that this is not the case for non-bank lenders. They price idiosyncratic risk slightly less than aggregate risk, the respective coefficients being 55.24 and 62.09. This is consistent with Hypothesis 2. The results for non-lenders are in fact in accordance with portfolio theory in the presence of constraints to diversifications in that aggregate risk requires a positive compensation and that this compensation should be larger than for idiosyncratic risk (the coefficient on aggregate risk, however, is only marginally larger than for idiosyncratic risk). All in all, this regression provides strong evidence for our main hypothesis in that the underpricing of risk is unique to the group of lenders to which public guarantees predominantly apply.

A potential problem with this comparison between banks and non-banks is that the group of lenders they are serving is not the same. In fact, it has been pointed out that banks serve safer borrowers whereas finance companies often cater to more risky firms (Carey, Post and Sharpe (1998)). This is also reflected in our sample. The first

[19] Banks where the primary beneficiary of the bailouts during the crisis of 2007-2009: 79% of the recipients of bailouts were banks. By contrast, only 4 finance companies (which dominate our non-bank sample) have received bailouts.(source: ProPublica bailout tracker).

[20] The number of bank loan observations is greater than in the baseline regression because we now have fewer controls and hence fewer missing observations.

three columns of Table 6 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 risk, smaller size, higher leverage and lower profitability.

The specialization of lenders into different borrower clienteles, however, is unlikely to bias our findings. First, estimating the loan pricing models separately for bank loans and non-bank loans means that we are only exploiting variation within each group of lenders, and not across lenders. Second, it is not obvious how a selection of riskier borrowers could explain the fact that banks charge a negative compensation for aggregate risk. In addition, we employ propensity score matching to reduce concerns about selection problems. Specifically, we take the pool of loans by 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 based on observable firm controls.

We first estimate a Probit model to predict the likelihood of a firm borrowing from a non-bank lender. In this regression, the dependent variable takes the value of one for a non-bank lender, and zero if the lender is a bank. The Probit regression includes idiosyncratic and aggregate risk, firm-specific controls, industry dummies, and year dummies. The results are presented in column (1) of Table 7, which show that idiosyncratic risk, leverage, profitability and market-to-book value influence the likelihood of borrowing from a non-bank lender. Next, we use the propensity score obtained from the Probit to match each non-bank to its nearest neighbor. To avoid bad matches, we impose a tolerance level of 0.05% on the maximum propensity score distance. Observations that are outside this range are dropped from the analysis. We end up with a sample of 1574 pairs of matched non-bank and bank loans.

We carry out two diagnostic tests to verify that the assumption of conditional independence, which states that after matching the choice of lender type is randomly assigned, is met. First, we re-estimate the Probit model restricted to the matched

sample (Table 7, column (2)). None of the explanatory variables are significant. Second, we conduct the univariate comparisons of firms' characteristics after matching in the last three columns of Table 6. None of the observable differences of the borrowers is statistically significant.

The last two columns of Table 5 report the loan pricing regressions for the matched group of firms. The results are very similar to that of the unmatched sample. Non-bank lenders price aggregate risk slightly higher than idiosyncratic risk, while banks offer lower loan spreads when aggregate risk increases.

We thus conclude that a pricing pattern consistent with systemic risk-taking only appears in the cohort of lenders with high public guarantees, while it is absent in the group of lenders that is less likely to benefit from public guarantees. This provides evidence for the hypothesis that the underpricing of aggregate risk is related to public guarantees.

Small banks

There is an extant literature on the "too-big-to fail" guarantee. Large banks are systemic simply because of their size and hence regularly benefit from public interventions, such as bail-outs. These banks have lower incentives to take on aggregate risk in order to increase the likelihood of benefitting from guarantees, as they are already protected. A theoretical prediction of Acharya and Yorulmazer (2007) is thus that systemic risk-taking incentives are stronger at small banks.

To investigate this, we construct a dummy variable *SmallBk* that equals one if bank size is below the median value of the sample, and zero otherwise. We first run a regression where the bank dummy is interacted with borrowers' risk measures:

$$LoanSpread_{i,f,b,t} = c + \alpha_1 IdioRisk_{i,t-1} + \alpha_2 AggRisk_{i,t-1} + \alpha_3 IdioRisk_{i,t-1} \times SmallBK_{b,t-1} + \alpha_4 AggRisk_{i,t-1} \times SmallBK_{b,t-1} +$$

$$\alpha_5 SmallBK_{b,t-1} + \sum_j \gamma_j \boldsymbol{Firm}_{i,j,t-1} + \sum_k \theta_k \boldsymbol{Loan}_{f,k,t} + \sum_n \varphi_n \boldsymbol{Bank}_{b,n,t-1} + \sum_t \delta_t T_t + \epsilon_{i,f,b,t}$$

The first column of Table 8 reports the result. Small banks on average do not charge very different spreads than large banks, the coefficient on the *SmallBk* dummy is 12.51 and only weakly significant. In addition, small banks charge a lower compensation for risk overall, as both interaction effects are negative and significant. However, small banks charge relatively less for aggregate risk than for idiosyncratic risk: the respective coefficients on the interaction effects are -56.70 and -22.13. This lends support for Hypothesis 3.

To relax the restrictions of identical coefficients on the control variables in the two subgroups, we next divide the sample into the two subgroups. The results (column (2) and (3) of Table 8) show that large banks do not charge a significantly negative compensation for aggregate risk, while small banks do. In addition, small banks underprice aggregate risk relative to idiosyncratic risk more than large banks do: the underpricing is -146.0 and -129.6, respectively.

Uncorrelated banks

Similarly to large banks, banks that are fairly correlated with the rest of the banking system are already protected by public guarantees. Instead of a “too-big-to-fail”, they benefit from “too-many-to-fail” (Acharya and Yorulmazer (2007)). If government guarantees are behind the underpricing of systemic risk, we would thus expect the underpricing to be more pronounced for uncorrelated banks.

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 risk measures, we estimate the following model:

$$LoanSpread_{i,f,b,t} = c + \alpha_1 IdioRisk_{i,t-1} + \alpha_2 AggRisk_{i,t-1} + \alpha_3 IdioRisk_{i,t-1} \times LowCorrBK_{b,t-1} + \alpha_4 AggVol_{i,t-1} \times LowCorrBK_{b,t-1} + \alpha_5 LowCorrBK_{b,t-1} + \sum_j \gamma_j \boldsymbol{Firm}_{i,j,t-1} + \sum_k \theta_k \boldsymbol{Loan}_{f,k,t} + \sum_n \varphi_n \boldsymbol{Bank}_{b,n,t-1} + \sum_t \delta_t T_t + \epsilon_{i,f,b,t}$$

The results are presented in column (4) in Table 8. The sample is now slightly smaller than in the baseline model since the data on the S&P 500 banking sector index starts only in the last quarter of 1989. The coefficient on the low correlation dummy is insignificant, indicating that bank correlation does not affect the overall level of loan pricing. The interaction effect of the dummy with idiosyncratic risk is positive (and marginally significant), whereas the interaction effect with aggregate risk is negative and significant. Taken together, this confirms Hypothesis 4 in that uncorrelated banks underprice aggregate risk more than correlated banks. Column (5) and (6) report next the result of a sample split. Aggregate risk is not significantly priced in the group of correlated banks, while there is still significant negative pricing among the uncorrelated banks. In relative terms, the underpricing is again stronger for uncorrelated banks.

Low external support

The last subsections have considered proxies for how likely banks are expected to receive support in the event of distress. Fitch support ratings provides a more direct measure of support expectations (e.g., Mariathasan, Merrouche and Werger (2014)). The support rating measures the likelihood that a bank can rely on external support when it is in danger of defaulting on its obligations. Besides from public authorities, such support can also come from the bank's shareholders. Banks that already enjoy high levels of external support – regardless of its source –have lower incentives to increase exposure to "too-many-to fail" guarantees, and should hence underprice aggregate risk less.

We construct a dummy variable *WeakSupport* that equals one if a bank's probability of external support is considered moderate, limited or unreliable (Fitch support rating takes values of 3 or 4 or 5). By contrast, the dummy equals zero if a bank's probability of external support is extremely high or high (Fitch support rating takes values of 1 or 2). Interacting the bank support dummy with borrowers' equity risk measures, we estimate the following model:

$$LoanSpread_{i,f,b,t} = c + \alpha_1 IdioRisk_{i,t-1} + \alpha_2 AggRisk_{i,t-1} + \alpha_3 IdioRisk_{i,t-1} \times WeakSupport_{b,t-1} + \alpha_4 AggVol_{i,t-1} \times LWeakSupport_{b,t-1} + \alpha_5 WeakSupport_{b,t-1} + \sum_j \gamma_j \boldsymbol{Firm}_{i,j,t-1} + \sum_k \theta_k \boldsymbol{Loan}_{f,k,t} + \sum_n \varphi_n \boldsymbol{Bank}_{b,n,t-1} + \sum_t \delta_t T_t + \epsilon_{i,f,b,t}$$

The results are presented in column (7) in Table 8. The sample is significantly smaller than in the baseline model as Fitch support ratings are only available for a subset of banks. The coefficient on the weak support dummy is positive and (weakly) significant, indicating that external support lowers loan spreads. The interaction effect of the dummy with idiosyncratic risk is insignificant, whereas the interaction effect with aggregate risk is negative and significant. Taken together, this confirms Hypothesis 5 in that banks with weak external support underprice aggregate risk more than strongly supported banks. Column (8) and (9) report next the result of a sample split. There is no difference in the pricing of idiosyncratic risk among both group of banks. Aggregate risk is not significantly priced in the group of banks with strong support, while there is significant negative pricing among the banks with low probability of external support. In relative terms, the underpricing is thus stronger for weakly supported banks.

This section has studied subgroups of lenders that have different expectations of receiving guarantees in the event of distress. In all cases we have found the underpricing of aggregate risk to be stronger among the lenders that, given the level of external support they already enjoy, benefit more from exposing themselves to too-

many-to fail guarantees. This provides support for our main hypothesis that the documented loan pricing pattern is driven by systemic guarantees.

5. Conclusions and Policy Implications

This paper has documented evidence for risk-taking arising from systemic subsidies, that is, subsidies obtained by weak banks during system-wide crises. Examining the syndicated loan market, we have found that loan spreads charged by banks are positively associated with borrowers' idiosyncratic risk but negatively associated with aggregate risk. The pricing of aggregate relative to idiosyncratic risk is inconsistent with standard portfolio theory but is explained by a preference for aggregate risk in an environment with too-many-to-fail guarantees. For a comparable set of loans issued by non-bank lenders that are less likely to be protected by public guarantees, the results are found to be consistent with standard theory. Further corroborating evidence comes from analyzing bank lenders that benefit less from increasing their exposures to guarantees; the results are weaker in these groups of lenders.

Based on our estimates we can calculate a value for the size of the guarantee. Theory suggests that, in the absence of public guarantees, the required compensation for aggregate risk should be at least as high as for idiosyncratic risk (these priors are confirmed for our sample of non-bank lenders). An estimate of the subsidy at the loan level can hence be obtained by multiplying a firm's aggregate risk with the estimated difference in the coefficients of idiosyncratic and aggregate risk, as we did in Section 4. This yields an average subsidy per loan of 16 bps ((91.7-(-42.7))*0.12). In other words, if banks had priced aggregate risk in the same way as idiosyncratic risk, loan spreads would be 16 bps higher. This number is only a lower bound for the total subsidy for two reasons. First, banks will only partially pass on the benefit from guarantees to borrowers (a complete pass-through is only expected in fully competitive markets and when all banks benefit equally from the guarantees). Second, the guarantee is also

likely to be passed on to other stakeholders of the bank. For instance, excessive maturity transformation arising from systemic risk (e.g., Farhi and Tirole (2012)) suggests that similar effects may arise in the pricing of the bank liabilities.

By assuming that the pricing of the subsidy into syndicated loans is representative for loans overall,[21] we can calculate the total subsidy. Outstanding loans at U.S. commercial banks were about 6.400 bln USD at the end of 2014, giving us a total (annual) subsidy of 10 bln USD (=6.400*0.0016), about 0.6% of bank equity (1.600 bln USD in 2014). Thus, the lower bound already suggest a sizeable impact. The number is smaller, though, than estimates for too-big-to-fail guarantees. For instance, Acharya, Enginer and Warburton (2013) estimate the implicit subsidy provided to large institutions ("too-many-to-fail") to be about 30 billion USD annually.

The estimated impact on loan pricing points to a considerable moral hazard problem arising from too-many-to-fail guarantees. Current macroprudential regulation aiming at mitigating moral hazard from public guarantees does not explicitly take into account too-many-to fail. For instance, the new Basel accord considers capital surcharges for banks that are large, interconnected and complex. In order to reduce moral hazard arising from too-many-to fail, surcharges for institutions that take on correlated risks may also need to be considered.

The pricing of public guarantees into loans has some further noteworthy implications. First, it suggests that the benefits from such guarantees do not exclusively accrue to banks; the real economy benefits as well. This adds a new angle to the policy debate that has viewed guarantees as private benefits to banks only (and which has led to the introduction of targeted levies for banks, such as the financial transaction tax in the European Union). A pass-through of the benefits to bank stakeholders is fully consistent, though, with the standard theory of industrial

[21] Obviously a big assumption, but we do not have clear priors as to whether the pass-through of the subsidy should be larger or smaller for other types of loans – so this remains the best guess.

organization. Thus, public guarantees for banks can have positive side-effects by stimulating economic activity.

Second, our analysis indicates that not all lenders benefit equally. Systemic guarantees lead to an underpricing of aggregate risk only. Given that borrowers compete with each other for scarce funds, firms that have a larger share of idiosyncratic risk may thus lose at the cost of firms with predominantly aggregate exposures. This reduces the efficiency of capital allocation in the economy. Since young and small firms typically have a larger share of idiosyncratic risks, firms that are thought to more than proportionally contribute to the value added in the economy may hence suffer.

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Table 1: Summary statistics

	Observations	Mean	Std Dev	Min	Median	Max
LoanSpread	11317	206.80	119.85	20.00	200.00	578.08
TotalRisk	11317	0.58	0.30	0.17	0.50	1.71
AggRiskShare	11317	0.23	0.17	-0.22	0.20	0.81
MarketVol	11317	0.15	0.06	0.08	0.13	0.40
IdioRisk	11317	0.55	0.30	0.15	0.48	1.70
AggRisk	11317	0.12	0.10	-0.05	0.10	0.53
IdioRisk_FF	11317	0.55	0.30	0.15	0.47	1.69
AggRisk_FF	11315	0.15	0.10	0.02	0.13	0.58
Beta	11317	0.76	0.56	-0.43	0.69	2.47
Log(SALES)	11317	5.61	1.73	1.63	5.56	9.85
Leverage	11317	28.03	20.69	0.00	26.60	92.86
ProfMargin	11317	-0.87	22.05	-149.97	3.21	28.59
ROA	11317	12.19	11.01	-35.07	12.82	39.98
NWC	11317	21.12	20.81	-28.73	19.31	74.22
Tangibales	11317	69.01	36.65	5.67	66.80	177.55
MktBook	11317	1.78	1.07	0.67	1.45	6.81
Business line diversification	10371	0.19	0.26	0.00	0.00	0.89
Geographic diversification	10533	0.16	0.23	0.00	0.00	0.89
Log(FacilitySize)	11317	3.80	1.77	-3.00	3.91	10.09
Maturity	11317	3.59	2.10	0.08	3.08	23.00
#Lenders	11317	6.05	7.72	1	3	113
#Facilities	11317	1.75	0.98	1	1	8
Revolver	11317	0.73	0.44	0	1	1
Termloan	11317	0.24	0.43	0	0	1
Senior	11317	1.00	0.04	0	1	1
Secured	11317	0.75	0.43	0	1	1
Corporate Purpose	11317	0.23	0.42	0	0	1
Debt Repayment	11317	0.17	0.37	0	0	1
Takeover	11317	0.25	0.43	0	0	1
Working Capital	11317	0.13	0.33	0	0	1
Other Purpose	11317	0.23	0.42	0	0	1
SizeBk	11317	11.27	1.88	6.22	11.31	14.36
CapitalBk	11317	7.52	1.94	3.59	7.25	14.89
ROABk	11317	0.95	0.58	-1.69	1.04	2.21
ZScoreBk	11317	3.18	0.46	0.89	3.25	4.03
NPLBk	11317	0.94	1.02	0.00	0.56	4.91
LiquidityBk	11317	18.72	8.57	3.92	18.15	46.14
LoanGrowthBk	11317	20.48	38.35	-35.73	9.19	199.01
CostOfFundBk	11317	3.39	1.65	0.52	3.31	10.52
InterbankCorr	9321	0.73	0.16	-0.27	0.78	0.98
Support	3452	3.42	1.67	1	4	5

Table 2: The pricing of loans by banks

The dependent variable is the all-in-drawn spread. Column (1) includes measures of idiosyncratic and aggregate risks. Column (2) also includes firm controls. Column (3) further includes loan controls. Column (4) includes all controls. Standard errors are adjusted for clustering at the bank level and reported in parentheses below the coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	No controls	Firm controls	Loan controls	Bank controls
	(1)	(2)	(3)	(4)
IdioRisk	216.52***	129.22***	92.55***	91.72***
	(9.00)	(7.20)	(6.12)	(6.12)
AggRisk	-172.94***	-54.34***	-40.69***	-42.72***
	(20.37)	(15.43)	(14.24)	(14.16)
Log(Sales)		-20.76***	-6.44***	-5.95***
		(1.24)	(0.91)	(0.93)
Leverage		0.98***	0.67***	0.68***
		(0.08)	(0.07)	(0.06)
ProfMargin		0.10	0.11	0.11
		(0.10)	(0.08)	(0.08)
ROA		-1.59***	-1.58***	-1.51***
		(0.24)	(0.17)	(0.14)
NWC		-0.25***	-0.25***	-0.26***
		(0.07)	(0.06)	(0.06)
Tangibles		-0.13***	-0.03	-0.04
		(0.04)	(0.03)	(0.03)
MktBook		-5.99***	-1.05	-1.45
		(1.90)	(1.21)	(1.01)
Log(FacilitySize)			-9.57***	-8.56***
			(1.50)	(1.30)
Maturity			-4.13***	-4.00***
			(0.90)	(0.88)
#Lenders			-0.49***	-0.57***
			(0.17)	(0.16)
#Facilities			12.36***	12.69***
			(1.75)	(1.72)
Revolver			-38.81***	-38.58***
			(9.09)	(8.89)
Termloan			-8.60	-8.14
			(10.43)	(10.25)
Senior			-189.94***	-193.14***
			(33.65)	(33.66)
Secured			72.59***	72.16***
			(2.75)	(2.61)
SizeBk				-4.32***
				(1.26)

CapitalBk				-2.43***
				(0.92)
ROABk				1.22
				(3.20)
ZscoreBk				-2.26
				(3.72)
NPLBk				3.65*
				(2.15)
LiquidityBk				-0.27
				(0.23)
LoanGrowthBk				-0.07**
				(0.03)
CostofFundBk				-3.12
				(2.74)
Constant	171.38***	312.27***	422.10***	490.87***
	(12.73)	(13.30)	(36.26)	(40.42)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	No	Yes	Yes	Yes
Purpose dummies	No	No	Yes	Yes
SE Clustered at banks	Yes	Yes	Yes	Yes
N	11317	11317	11317	11317
adj. R-sq	0.341	0.440	0.557	0.561

Table 3: Robustness

The dependent variable in all specifications is the all-in-drawn spread. Column (1) considers a risk decomposition based on the Fama-French model. Column (2) uses the S&P 500 banking sector index as the benchmark portfolio in the decomposition. Column (3) uses unlevered equity risk. Column (4) uses total risk and share of aggregate risk in total risk. Column (5) excludes loans originated by lenders and borrowers within the same state. Column (6) estimates panel regressions with firm fixed effects. Column (7) estimates a bank fixed effects model. Standard errors are adjusted for clustering at the lender level in all specifications except in column (6) clustering at the borrower level and are reported in parentheses below coefficients. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

	Fama French decomposition	Bank index decomposition	Unlevered risk	Share of aggr. Risk	Interstate lending	Firm FE	Bank FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$IdioRisk^{FF}$	91.07***						
	(6.00)						
$AggRisk^{FF}$	-23.00						
	(15.46)						
$IdioRisk^{Bank}$		93.19***					
		(6.23)					
$AggRisk^{Bank}$		-64.02***					
		(16.02)					
Unlev. IdioRisk			70.49***				
			(8.31)				
Unlev. AggRisk			-88.68***				
			(13.43)				
TotalRisk				82.55***			
				(6.39)			
AggRiskShare				-64.14***			
				(6.85)			
IdioRisk					97.42***	104.25***	93.03***
					(6.57)	(8.79)	(7.11)
AggRisk					-25.75	-47.61**	-49.55***
					(16.97)	(19.29)	(15.20)
Constant	492.95***	509.02***	522.63***	500.04***	463.74***	452.74***	423.08***
	(40.89)	(42.74)	(39.91)	(40.54)	(49.03)	(63.32)	(65.87)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered at banks	Yes	Yes	Yes	Yes	Yes	No	Yes
SE Clustered at firms	No	No	No	No	No	Yes	No
N	11315	10700	11317	11317	8294	11317	11317
adj. R-sq	0.561	0.57	0.544	0.563	0.562	0.33	0.493

Table 4: IV estimation

Columns (1) and (3) report the first stage regression where 1-HHI index of business lines and 1-HHI index of geographic diversification are used to instrument the share of aggregate risk and aggregate risk, respectively. Columns (2) and (4) report the second stage regressions in which the all-in-drawn spread is the dependent variable. Standard errors are adjusted for clustering at the bank level and are reported in parentheses below the coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	IV for s AggRiskShare		IV for AggRisk	
	1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)	(3)	(4)
TotalRisk	-0.04***	78.49***		
	(0.01)	(7.71)		
AggRiskShare		-136.76*		
		(75.73)		
IdioRisk			0.08***	110.89***
			(0.01)	(13.36)
AggRisk				-298.79**
				(151.96)
Business line diversification	0.03***		0.01	
	(0.01)		(0.00)	
Geographic diversification	0.04***		0.03***	
	(0.01)		(0.01)	
Year dummies	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes
SE Clustered at banks	Yes	Yes	Yes	Yes
N	10166	10166	10166	10166
adj. R-sq	0.52	0.56	0.40	0.54
F-test	26.24		14.4	
Underidentification		0.00		0.00
Hansen J		0.11		0.25

Table 5: Non-bank lenders

The dependent variable is the all-in-drawn spread. Column (1) reports results for the sample of banks. Column (2) reports results for the sample of non-banks. Column (3) and (4) report results from a matched sample of firms. Standard errors are adjusted for clustering at the bank level and are reported in parentheses below the coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Full sample		PSM sample	
	Bank	Nonbank	Bank	Nonbank
	(1)	(2)	(3)	(4)
IdioRisk	92.62***	55.19***	95.61***	59.58***
	(5.84)	(11.79)	(12.08)	(16.11)
AggRisk	-37.73***	62.41*	-71.01***	73.97**
	(13.99)	(32.60)	(22.04)	(35.61)
Constant	490.58***	481.57***	451.34***	634.55***
	(43.19)	(98.49)	(56.62)	(97.78)
Year dummies	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
SE Clustered at banks	Yes	Yes	Yes	Yes
N	12233	1789	1549	1549
adj. R-sq	0.540	0.342	0.461	0.347

Table 6: Test for equality of means

Column (1) and (2) report the sample means of variables for banks and non-banks. Column (3) reports the corresponding t-test of coefficient equality. Column (4) and (5) report the sample means of variables for the matched sample of banks and non-banks. Column (6) reports the corresponding t-test of coefficient equality. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Unmatched sample			Matched sample		
	Bank	Nonbank	Difference in means	Bank	Nonbank	Difference in means
	(1)	(2)	(3)	(4)	(5)	(6)
IdioRisk	0.56	0.82	-0.26***	0.74	0.74	0.00
AggRisk	0.12	0.11	0.00*	0.11	0.11	0.00
Log(Sales)	5.58	5.10	0.48***	5.06	5.16	-0.09
Leverage	28.16	33.89	-5.73***	31.81	32.61	-0.81
ProfMargin	-0.94	-9.76	8.83***	-8.85	-8.92	0.08
ROA	12.11	5.04	7.07***	6.34	6.33	0.01
NWC	21.04	19.00	2.03***	21.12	20.00	1.12
Tangibles	69.48	69.89	-0.411	68.63	69.15	-0.52
MktBook	1.77	1.51	0.26***	1.57	1.55	0.02
Observations	12233	1796	14091	1549	1549	3098

Table 7: Propensity score regressions

Column (1) reports a Probit regression that explains whether a loan is originated for a non-bank lender using the entire sample. Column (2) reports the Probit regression for the matched sample of firms. 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.

	Prematch	Postmatch
	(1)	(2)
IdioRisk	0.9326***	-0.0039
	(0.0995)	(0.1412)
AggRisk	-0.2803	0.0993
	(0.2839)	(0.3947)
Log(Sales)	-0.0324	0.0293
	(0.0299)	(0.0428)
Leverage	0.0058***	0.0005
	(0.0014)	(0.0018)
ProfMargin	0.0028***	-0.0003
	(0.0010)	(0.0013)
ROA	-0.0183***	-0.0000
	(0.0045)	(0.0059)
NWC	0.0001	-0.0015
	(0.0015)	(0.0019)
Tangibles	-0.0001	-0.0001
	(0.0008)	(0.0010)
MktBook	-0.0888***	-0.0034
	(0.0286)	(0.0369)
Constant	-1.9482***	-0.5511
	(0.4367)	(0.8002)
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
N	14027	3098
p-value of Chi2	0.0000	0.9998
Pseudo R-sq	0.1290	0.0072

Table 8: Bank size, correlation and external support

The dependent variable is the all-in-drawn spread. Column (1) reports result for the full sample of small and large banks. Columns (2) and (3) contain results for the subsample of small and large banks, respectively. Column (4) reports results for the full sample of low and high correlation banks. Columns (5) and (6) contain results for the subsample of low and high correlation banks, respectively. Column (7) reports results for the full sample of weakly and strongly supported banks. Columns (8) and (9) contain results for the subsample of weakly and strongly supported banks, respectively. Standard errors are adjusted for clustering at the bank level and are reported in parentheses below the coefficients. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	Full sample	Small banks	Large banks	Full sample	Low correlation	High correlation	Full sample	Weak supported	Strong support
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IdioRisk	106.09***	77.76***	113.59***	88.26***	87.97***	101.94***	99.15***	101.99***	101.89***
	(7.19)	(6.78)	(9.29)	(9.16)	(8.61)	(11.22)	(16.63)	(19.41)	(21.20)
AggRisk	-14.75	-68.32***	-16.09	-13.04	-63.21***	-21.80	26.03	-51.02***	44.59
	(17.36)	(15.15)	(15.99)	(18.01)	(20.35)	(16.61)	(28.40)	(18.38)	(28.79)
IdioRisk*Small	-22.13***								
	(7.93)								
AggRisk*Small	-56.70***								
	(21.72)								
Small	12.51*								
	(7.47)								
IdioRisk*LowCorrBK				14.60*					
				(8.08)					
AggRisk*LowCorrBK				-55.71**					
				(26.46)					
LowCorrBK				2.34					
				(5.74)					

IdioRisk*WeakSupport							2.12		
							(18.58)		
AggRisk*WeakSupport							-68.86**		
							(33.69)		
WeakSupport							22.43*		
							(11.40)		
Constant	506.79***	468.84***	464.75***	531.39***	393.01***	647.81***	571.39***	485.54***	714.67***
	(48.05)	(57.71)	(77.86)	(50.52)	(114.21)	(61.25)	(78.74)	(72.92)	(92.52)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered at banks	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11317	5649	5668	9321	4658	4663	3452	2250	1202
adj. R-sq	0.562	0.517	0.580	0.572	0.592	0.564	0.572	0.541	0.619

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
IdioRisk	Idiosyncratic risk using one factor CAPM regressions. Defined as the standard deviation of the residual.	CRSP
AggRisk	Aggregate risk using one factor CAPM regressions. Defined as the product of beta and market volatility.	CRSP
Beta	Equity beta estimated from the CAPM.	CRSP
TotalRisk	Total equity volatility, dened as the standard deviation of daily excess return one year before the facility start date.	CRSP
$IdioRisk^{FF}$	Idiosyncratic riskfrom Fama French three-factor model. Defined as the standard deviation of the residual.	CRSP, WRDS
$AggRisk^{FF}$	Aggregate risk from Fama French three-factor model. Defined as the product of market beta and market volatility.	CRSP, WRDS
$IdioRisk^{Bank}$	Idiosyncratic risk from one factor model where market portfolio is replaced by S&P 500 banking sector index. Defined as the standard deviation of the residual.	CRSP, Datastream
$AggRisk^{Bank}$	Aggregate risk from one factor model where market portfolio is replaced by S&P 500 banking sector index. Defined as the product of beta and banking sector index volatility.	CRSP, Datastream
Unlevered IdioRisk	Idiosyncratic risk using one factor CAPM regressions, unlevered by multiplying a ratio of equity/(debt+equity).	CRSP, Compustat
Unlevered AggRsik	Aggregate risk using one factor CAPM regressions, unlevered by multiplying a ratio of equity/(debt+equity).	CRSP, Compustat
AggRiskShare	A ratio of aggregate risk in CAPM regression over total equity volatility.	CRSP
Log(Sales)	Logarithm of rm sales at close of the borrower.	Dealscan
LEVERAGE	Firm leverage dened as sum of long term and short term debts over total assets of the borrower.	Compustat
PROFMARGIN	Prot 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

Business line diversification	1- business line HHI. HHI is calculated as the sum of the share of sales in various business lines of a firm.	Compustat Historical Segments
Geographic diversification	1- geographic HHI. HHI is calculated as the sum of the share of sales in various geographic areas of a firm.	Compustat Historical Segments
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
CORPURPOSES	Loan purpose dummy indicates loans borrowed for corporate purpose.	Dealscan
EPAYMENT	Loan purpose dummy indicates loans borrowed for debt repayment.	Dealscan
TAKEOVER	Loan purpose dummy indicates loans borrowed for takeover.	Dealscan
WORKCAPITAL	Loan purpose dummy indicates loans borrowed for working capital.	Dealscan
OTHERPURPOSES	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
ROABK	Return on assets 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
NPLBK	Nonperforming loans over gross loans of the lender.	Call reports, FR Y-9C
LiquidityBK	Liquid assets over total assets of the lender.	Call reports, FR Y-9C

LoanGrowthBK	Growth rates of gross loans 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
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
Support	Fitch support rating assigned on a five-point scale, with '1' representing an extremely high probability of support, and '5' indicating that support cannot be relied on	Fitch
WeakSupport	Dummy for weakly supported banks, of which Fitch support rating takes value of 3, or 4, or 5.	Fitch

Table A2: Composition of non-bank and bank sample

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			
Banks	12,130	4,402	567
Thrift or S&L	103	51	7
Total	12,233	4,453	574