Why Are Commercial Loan Rates So Sticky? The Effect of Private Information on Loan Spreads

CEM DEMIROGLU,[1] CHRISTOPHER JAMES,[2] and GUNER VELIOGLU[3]

First draft: August 28, 2018

This version: May 7, 2019

ABSTRACT

Past studies find that commercial loan spreads are "sticky," in the sense that they do not fully respond to changes in market rates or observable firm credit risk characteristics. In this paper, we provide evidence that stickiness arises, in part, because the intensity of bank screening based on private soft information varies with changes in credit market conditions and observable firm credit risk characteristics. Our analysis demonstrates that stickiness in loan spreads does not necessarily indicate loan mispricing and may arise even in the absence of credit rationing, bank information monopolies, or behavioral biases in loan contracting.

[1] Koç University, College of Administrative Sciences and Economics, Sariyer, Istanbul, Turkey 34450, phone: +90-212-338-1620, fax: +90-212-338-1653, e-mail: cdemiroglu@ku.edu.tr.

[2] University of Florida, Warrington College of Business, Gainesville, FL 32611-7168, phone: +1-352-392-3486, fax: 352-392-0301, e-mail: christopher.james@warrington.ufl.edu.

[3] Loyola University Chicago, Quinlan School of Business, Chicago, IL 60611, phone: +1-312-915-7815, e-mail: gvelioglu@luc.edu.

1. Introduction

A number of past studies have suggested that commercial loan rates are "sticky," in the sense that they only partially adjust to changes in market rates or firm credit risk characteristics. For example, Berger and Udell (1992) and Dougal, Engelberg, Parsons, and Van Wesep (2015) find, respectively, that commercial loan spreads are inversely related to open-market rates and the change in aggregate credit spreads since the borrower's prior loan. In addition, several studies provide evidence that the private information that banks gain through their initial due diligence and on-going monitoring allows relationship lenders to "hold up" borrowers, which can lead to downward rigidity in loan rates and the appearance of stickiness.[1]

Figure 1 provides an example of stickiness on loan spreads. Specifically, Figure 1 shows that the component of credit spreads that cannot be explained by loan or publicly observable firm credit risk characteristics is systematically related to whether credit spreads have fallen or risen since the firm's last loan. As shown, relative to the group of firms that did not experience any change in their credit spreads between two consecutive loans, firms that last borrowed when spreads were lower (higher) on average pay 7.6 (9.1) percent lower (higher) spreads in their new loan. This pattern in credit spreads is puzzling; why should borrowers with seemingly similar credit risk characteristics, borrowing for the same reason and receiving loans with the same security and covenant structure, borrow at different rates based on whether spreads have risen or fallen since their last loan?

Potential explanations for the type of stickiness shown in Figure 1 include credit rationing, hold-up problems arising from informed lenders' information monopolies, inter-temporal interest rate smoothing by relationship lenders, and behavioral biases such as loss aversion and

[1] See, for example, Rajan (1992), Santos and Winton (2008), and Schenone (2010).

anchoring.[2] A common component of these explanations is that informational frictions limit the impact of competitive forces on loan rates, which leads loan rates to stray from the levels based on fundamentals. As a result, it is argued that stickiness in loan rates reflects mispricing and thus is indicative of a misallocation of credit.

In this paper, we provide an explanation based on the time-varying importance of private information in loan pricing. Specifically, we argue that reliance by bank lenders on proprietary firm-specific information when negotiating loan rates can give rise to the appearance of loan rate stickiness. The basic idea is that, following increases in market-wide credit spreads or observed credit risk characteristics of a borrower, bank lenders engage in more intensive due diligence and monitoring, resulting in greater reliance on proprietary information when setting the terms of the borrower's new loan. Thus, the path of aggregate spreads between loans is related to current loan spreads because it reflects the quality of the lenders' private information. By linking stickiness to variations in the quality of private information relied upon in the lending process, our findings suggest that stickiness does not necessarily reflect loan mispricing or misallocation of credit. More important, our findings suggest important cross-sectional and time-series variation in the information produced by banks in the due diligence process.

We begin our empirical analysis by confirming the evidence in previous studies that loan spreads appear to be sticky, using a large sample of term loans and revolving lines of credit originated between 1987 and 2016 and recorded by Dealscan. Next, we investigate whether these results should be construed as evidence of loan mispricing. Put differently, do sticky loan rates indicate that loan spreads are influenced by factors other than fundamental credit risk?

Previous theoretical and empirical work suggests that the importance of bank screening is counter-cyclical; that is, the intensity of bank screening decreases during credit booms and

[2] See, for example, Fried and Howitt (1980), Sharpe (1990), Berger and Udell (1992), Boot (2000), Schenone (2010), and Dougal et al. (2015).

increases during credit contractions.[3] At the firm level, changes in credit risk may lead banks to engage in more intensive monitoring and screening, increasing the importance of private information as the financial performance of the firm declines. For example, ceteris paribus, the benefits of due diligence and monitoring are likely to be greater relative to their costs as the default risk of the borrower increases. We present a simple model to illustrate how variations in the quality of private information that are correlated with credit spreads can lead to the appearance of sticky loan rates. We refer to this explanation for stickiness as the *private information hypothesis*.

We conduct several tests of this hypothesis. First, we examine the stickiness of CDS spreads as a placebo test. The idea is that informational frictions or behavioral biases that have the potential to give rise to stickiness in commercial loan spreads should not generate stickiness in CDS spreads.[4] Overall, we find that CDS spreads appear to be sticky between two consecutive loan dates, but not between *randomly* selected equidistant non-loan dates. The stickiness in market-determined CDS spreads on loan dates suggests that material non-public information about firm credit risk is revealed to the market during the loan negotiation process, consistent with the *private information hypothesis*. Finding no stickiness in CDS spreads between randomly selected dates suggests that, for firms with CDS, stickiness in loan rates is unlikely to be a

[3] Dell'Ariccia and Marquez (2006) develop a model in which adverse selection problems create incentives for banks to screen loan applicants. Screening decreases during lending booms because of reduced adverse selection costs. Reduced screening, in turn, leads banks to reduce lending standards, resulting in deterioration in the credit quality of bank portfolios. Berger and Udell (2004) argue that, during credit booms, the quality of bank screening decreases, in part, due to the atrophying skills of experienced loan officers as time passes since their last problem-loans experience. As a result of this deterioration, officers may be less able to differentiate low-quality borrowers from high-quality borrowers. The deterioration, they argue, applies mostly to the accumulation and processing of soft non-quantitative information about borrowers (e.g., character and reliability), as opposed to hard quantitative information (e.g., financial ratios and credit scores). Becker, Bos, and Roszbach (2018) find that bank internal credit ratings are more informative about future defaults during economic downturns, suggesting that banks' sorting effectiveness is counter-cyclical.

[4] Because CDS are continuously priced in secondary markets, there is no clear historical reference price or transaction to anchor on when pricing CDS. Also, hold-up problems and inter-temporal smoothing that may affect loan rates should presumably not affect market-determined pricing of CDS.

manifestation of anchoring, holdup problems, or credit rationing. Finally, we find no stickiness in loan spreads once we control for CDS spreads, suggesting that previous estimates of stickiness might be upward biased due to omission of material non-public information that banks rely on during loan negotiations.

Our second test involves examining whether stickiness in loan rates is related to various proxies for the importance of private information in lending decisions. Past studies suggest that reliance on private information is greater for private firms than for publicly traded firms, for unrated than for rated firms, and for bank-dependent firms than for firms with access to public bond markets (see, for example, Sufi (2007, 2009), Santos and Winton (2008), and Schenone (2010)). Consistent with the private information hypothesis, we find significantly greater stickiness in the loan spreads of private firms, bank dependent firms, and unrated firms than the loan spreads of more transparent firms.

For our third test, we examine whether the evolution of loan spreads between loans predicts *future* changes in credit risk. If the quality of private information varies inversely with changes in credit spreads, then we expect spread evolution to be negatively related to future changes in credit risk. Consistent with our argument, we find that spread evolution is inversely related to future changes in credit risk. For example, positive values of spread evolution are associated with increases in credit risk during the three years after the loan date. Moreover, consistent with the *private information hypothesis*, we find that the predictive power of spread evolution varies with our proxies for firm opaqueness.

Our fourth test involves examining whether banks' reliance on soft information varies with credit market conditions. As Stein (2002) points out, bank lending decisions are a function of both hard and soft information that the lender obtains as part of the due diligence process. The private information hypothesis predicts that reliance on private information varies with credit spreads. To test this prediction, we follow Rajan, Seru, and Vig (2015) who measure time-series variation in banks' reliance on soft information using 1-R^2 of annual interest spread regressions modeled as a function of observable loan and borrower credit risk characteristics (i.e., hard information). The idea is that, greater reliance on soft information in loan pricing implies that observable credit risk measures have less of an impact on loan pricing, leading more unexplained heterogeneity in spreads and thus lower R^2s.

We compare R^2s of loan spread regressions estimated during periods when the Moody's Baa rated bond credit spreads are in the highest and lowest quartiles; and when credit market conditions are tight versus loose (determined based on the Federal Reserve's senior loan officer survey on bank lending practices). Consistent with significant time-series variations in banks' reliance on soft information in pricing commercial loans, we find that the R^2s are between 10% and 20% higher when aggregate credit spreads are low and when credit standards are tight. Consistent with the *private information hypothesis* we find that variations in R^2s over the credit cycle are greatest for relatively less transparent firms.

Overall, our findings are consistent with reliance on and the quality of private information varying with credit risk measures based on publicly available information. The results using firms with traded CDS suggest that loan rate stickiness for these firms does not imply mispricing. Because loan spreads for firms with traded CDS are significantly less sticky than spreads on loans to other firms in our sample, however, we cannot rule out that, for firms without CDS trading, stickiness may reflect mispricing. For example, stickiness may reflect hold-up problems since it is greater for relationship loans and for firms facing greater information frictions. Specifically, the greater the reliance on proprietary information in the lending process, the greater the potential for lenders to exploit their information advantage by raising rates above than what would be expected if information were symmetrically distributed between current lenders and potential lenders.

Our study is related to recent theoretical and empirical work on how bank lending standards vary over the business cycle. This literature mainly focuses on whether bank lending standards become more lax during credit booms.[5] We add to this literature by providing evidence that the intensity of bank screening varies with changes in firm credit risk. Our study is also related to recent research on how the informational value of financial intermediaries varies over the business cycle. For example, Loh and Stulz (2018) find that the value of sell-side analysts' forecasts increases during financial crises, and Frankel, Kothari, and Weber (2006) show that analyst forecasts are more informative when firm level uncertainty is greater. Our results suggest a similar pattern in bank screening which influences the evolution of credit spreads both in aggregate and at the firm level. Finally, our study contributes to the literature on tests for behavioral biases in financial markets. We show that tests for reference dependence or anchoring may be biased in favor of finding anchoring when the private information concerning quality varies with publicly observable measures of quality.

The remainder of the paper is organized as follows. In the next section, we describe the data used in the study. In Section 3, we confirm previous findings that loan spreads are sticky and show that CDS spreads on loan start dates are also sticky. To motivate our analysis of the role of private information in generating the appearance of stickiness in spreads, in Section 4, we present a simple model of the determination of loan spreads and illustrate how variations in private information can generate the appearance of stickiness in loan spreads. We then examine the relationship between loan rate stickiness and proxies for the reliance on private information in loan contracting. Section 5 provides our conclusions.

[5] See, for example, Gorton and He (2008), Mian and Sufi (2009), Keys, Mukherjee, Seru, and Vig (2010), Becker and Ivashina (2014), Murfin and Petersen (2016), and Rodano, Serrano-Velarde, and Tarantino (2018).

2. Data and Descriptive Statistics

2.1. Data

Our sample consists of term loans and revolving lines of credits in the Thomson Reuters Loan Pricing Corporation's (LPC) Dealscan database. Our sample period is between 1987 and 2016. We exclude loans taken out by non-US firms, financial firms and utilities (SIC codes 6000-6999 and 4900-4999, respectively), as well as loans denominated in foreign currencies and those that mature in less than a year. Because we are interested in how loan spreads evolve over time, we restrict the sample to firms that borrowed at least twice during our sample period. Moreover, following Dougal, Engelberg, Parsons, and Van Wesep (2015) (DEPV hereafter), we require the gap between consecutive loans to be at least one year.

We supplement Dealscan data with (i) annual borrower financials (as of the most recent fiscal year end preceding the loan date) from Compustat (public firms) and Capital IQ (private firms),[6] (ii) daily stock price information from the Center for Research in Security Prices (CRSP), (iii) loan ratings from S&P's RatingsXpress database, and (iv) daily CDS quotes (for five-year senior unsecured dollar-denominated obligations) from the Markit Group. We require non-missing data on firm and loan characteristics used in our loan pricing models.[7] We provide detailed variable definitions in Appendix D.

2.2. Descriptive Statistics

Table 1 provides descriptive statistics on borrower and loan characteristics. As shown in Panel A, our sample consists of 12,938 loans taken out by 3,290 firms. The median maturity of those loans is 60 months and the median all-in-drawn spread is 175 basis points. Because several of our tests involve examining the stickiness in market-determined CDS spreads, we report

---

[6] For the period before August 2012, we use Chava and Roberts (2008) linking file to merge Dealscan with Compustat. For the remaining period, we hand-match the two databases.

[7] See Appendix Table B.1 for the exact list of non-missing variables required for inclusion in our sample.

summary statistics separately for the subsample of firms with traded CDS. As shown, firms with traded CDS are much larger than other firms in the sample based on both average assets and sales, and they appear to be less risky based on both mean and median all-in-drawn spread.

In Panel B, we provide descriptive statistics on all-in-drawn spreads by credit rating and loan type. As shown, about half of our sample firms are unrated, and approximately 84% of the rated firms have a BBB, BB, or B rating. Not surprisingly, both the mean and median spread increase monotonically moving down in the rating spectrum. The mean and median spreads of unrated firms fall between those of firms rated BB and B. In addition, about 78% of our sample loans are revolving lines of credit and the balance are term loans. The former have lower mean all-in-drawn spreads than the latter (179 versus 273 basis points).[8]

3. Empirical Tests of Loan Rate Stickiness

First-generation studies that test for stickiness in loan rates rely on aggregate data. They regress average quarterly commercial loan rates on open-market interest rates and their lags to examine how fast loan rates respond to changes in open-market rates. For example, Goldfeld (1966) and Jaffee (1971) document that commercial loan rates are slow to adjust to changes in open-market rates, which they interpret as evidence of credit rationing. Berger and Udell (1992) extend those studies by using individual loan data that permits the use of various features of loan contracts to gain sharper insights about the origins of loan rate stickiness. Regressing commercial loan spreads on open market rates and a set of loan characteristics, they find the same degree of stickiness in loans that are issued under commitment, which insulate borrowers from rationing, and non-commitment loans; thus, they conclude that equilibrium credit rationing is not a significant macroeconomic phenomenon. They conjecture that stickiness may arise from

[8] This is in part because investment-grade firms tend to rely on revolving lines of credits as a back-up source of funding against liquidity shocks in the commercial paper market, but they rarely issue term loans.

relationship lenders providing implicit interest rate insurance by inter-temporally smoothing loan rates.

Berger and Udell (1992)'s loan data set does not feature unique borrower identifiers, nor does it contain detailed information on borrower financial characteristics. As a result, it is difficult to infer from their findings the extent to which stickiness reflects omitted variables bias, inter-temporal interest rate smoothing, hold-up problems, or anchoring on past credit spreads. In a recent study, DEPV overcome these data limitations using the Dealscan database which provides the history of loan contracts for large borrowers. DEPV conduct two separate tests of stickiness. First, using a simple model of credit spreads with interacted firm rating*loan type*year fixed effects, they examine whether the path of aggregate credit spreads since a borrower's previous loan affects the borrower's current loan spread. Second, using firm-specific credit histories, they test the effect of a firm's historical loan spreads on its current loan spread, after controlling for observable determinants of the current spread. Both tests indicate significant stickiness in loan spreads.

In this paper, we focus on DEPV's model of loan rate stickiness.[9] We focus on their model because, by examining loan rate stickiness between loans taken out by the same firm, we can control for time-invariant unobserved firm characteristics as well as changes in firm and loan risk characteristics between consecutive loans.[10]

3.1. Preliminary Results Using Changes in Aggregate Loan Spreads

[9] In the Appendix A, we provide evidence of stickiness in loan rates using the Berger and Udell (1992)'s model and show, in the context of their empirical model, that stickiness in loan spreads arises in part from omitted credit risk measures.

[10] DEPV test several alternative explanations of stickiness in loan rates. These include, relationship lending, changes in covenant structure (or other non-price deal terms), rounding in loan spreads, and non-competitive lending practices. The authors do not find a significant evidence that any of these explain stickiness. In unreported results, we confirm DEPVs finding that these factors do not explain stickiness.

In this section, we provide preliminary evidence that time-series variation in banks' reliance on proprietary soft information gives rise to the appearance of stickiness in loan spreads. Specifically, we examine the relationship between the current loan spread and the change in aggregate spreads since the borrower's previous loan. We proceed in three steps. First, we confirm the evidence in DEPV that the current spread is inversely related to the change in aggregate spread. Second, we apply the same methodology to examine the stickiness of CDS spreads—as discussed in greater length below, if stickiness arises from informational frictions such as bank information monopolies or behavioral biases such as anchoring, we expect to observe stickiness in loan spreads but not in market-determined CDS spreads. Finally, we examine whether loan spreads continue to exhibit stickiness when we control for borrowers' CDS spreads at the time of the loan to account for market information not yet reflected in firm financial characteristics and thus minimize potential measurement errors in credit risk.

We start this analysis by calculating the annual average loan spread separately for each loan type (term loan and revolving line of credit) and firm-level S&P credit rating (AAA/AA, A, BBB, BB, B, CCC or worse, unrated) pair, resulting in a total of 14 time-series indices of aggregate credit spreads. Next, we assign each firm into the relevant index based on its rating and loan type in the year it takes out a loan, and then calculate the change in the log of index level between the year of the current loan and the year of the firm's prior loan, *ΔAgg. Log(Loan spread)*. Finally, we regress the log of the current loan spread on *ΔAgg. Log(Loan spread)* and year*loan type*firm rating fixed effects. We include the interaction between loan year and firm rating, instead of including these variables separately, to allow for the effect of ratings on loan spreads to vary over time, hence account for cyclical variations in ratings criteria.

As shown in Column 1 of Table 2, we find that spreads are significantly related to changes in aggregate spreads, i.e., they appear to be sticky. For example, we find that the coefficient estimate on *ΔAgg. Log(Loan spread)* is -0.14, indicating that, on average, 86% of the change in aggregate credit spreads is reflected into the current loan spread while the remaining 14% is not.

One explanation for finding a significant effect of *ΔAgg. Log(Loan spread)* on the current loan spread is that *ΔAgg. Log(Loan spread)* picks up credit risk characteristics that are omitted from the model in Column 1. While we attempt to control for credit risk using ratings fixed effects, ratings may not fully reflect the riskiness of the loan. As Murfin and Petersen (2016) point out, the risk reflected in credit ratings may not map one-to-one with loan spreads. There are several reasons why this may occur. First, suppliers of loans may possess better information concerning the riskiness of their borrowers than rating agencies do. Second, rating agencies often respond to changes in credit risk with a delay due to concerns about maintaining ratings stability, and thus credit ratings may not be a timely measure of credit risk. Third, as shown in Table 1, most of the firms in our sample are unrated, and thus rating fixed effects do not capture the variation in credit risk among unrated firms. Finally, S&P ratings are used to control for credit risk, but those ratings only reflect S&P's estimates of the likelihood of default, not expected credit losses conditional on default. In contrast, loan spread should reflect both the likelihood of default as well as loss given default.

One way to address concerns with mis-measurement of credit risk is to examine the stickiness of CDS spreads on loan dates. As Murfin and Petersen (2016, p. 309) point out, CDS spreads should impound any information that the market, and thus the lenders, have about the borrower. Moreover, they note, "…because CDS are themselves risk premiums, they control for both the probability of default and the covariance of expected cash flows on borrower loans/bond discount rates."

The test of stickiness in CDS spreads also helps to evaluate whether mispricing arising from anchoring or other frictions in the primary loan market can explain the stickiness in loan spreads. For non-traded loans, the spread (at origination) of the firm's previous loan could be a natural reference price to anchor on. However, because CDS are priced continuously in secondary markets, for CDS, there is no clear historical reference transaction or price. Thus, if stickiness arises from anchoring, we should find no stickiness in CDS spreads. Moreover, because hold-up problems and inter-temporal interest rate smoothing, alternative explanations for loan rate stickiness, are unlikely to influence the pricing of CDS, finding stickiness in CDS spreads would suggest that stickiness in loan rates may arise even in the absence of these frictions.

Overall, as shown in Column 2 of Table 2, we find that CDS spreads are as sticky as loan spreads. For example, the coefficient estimate on the change in aggregate spreads is -0.14 for CDS spreads and statistically significant at the 1% level. Moreover, as shown in Column 3, controlling for CDS spreads, we find very little evidence that loan spreads are sticky. For example, when the CDS spread on the facility start date is used as a control, the coefficient estimate on *ΔAgg. Log(Loan spread)* drops to zero. Overall, these results indicate that incomplete or imperfect measurement of borrower risk may give rise to the appearance of stickiness in loan spreads, when a model like the one in Table 2 is to test for stickiness.

3.2. *Testing for Stickiness in Loan Rates Using Borrowers' Past Loan Spreads*

Another, more refined, test of stickiness involves examining the relevance of borrowers' past spreads in determining the spreads on current loans. Specifically, DEPV use Genesove and Mayer (2001)'s two-stage repeat sales pricing model that was originally developed to test for loss aversion in residential real estate markets. The same model was later used by Beggs and Graddy (2009) to test for evidence of anchoring in the collectible art market. The advantage of this model, relative to the models in Table 2, is that it allows for the inclusion of firm- and loan-level controls which help mitigate (but not eliminate) concerns about mis-measurement of credit risk. However, as discussed below, an important drawback of the model is that identification depends on the effect of private information concerning the creditworthiness of the borrower remaining the same between the two loan dates. In other words, the model assumes that any unobserved credit risk relevant private information does not vary over time.[11]

The first stage of the two-stage estimation procedure involves regressing the realized (or actual) loan spread, s, on a set of observable loan and borrower characteristics, and use the regression estimates to calculate a predicted spread, $\hat{s}$, for each loan. We follow DEPV and use the same set of control variables in the first-stage spread model as the ones used in Ivashina (2009). We also follow DEPV and estimate a separate first-stage loan spread model each year to allow for the regression coefficients to vary over time.

In the second stage, we estimate the following specification:

$$s_{i,t} = \beta \hat{s}_{i,t} + \delta(s_{i,r} - \hat{s}_{i,t}) + \gamma(s_{i,r} - \hat{s}_{i,r}) + \varepsilon_{i,t}. \tag{1}$$

Here, the current time is denoted t, and the date of the firm's prior loan financing r. The first term, β, captures the effect of time *t* observables on the realized time *t* spread, $s_{i,t}$. If the first-stage model is a good predictor of realized spreads, β should be close to 1. The second term, δ, is the coefficient on the spread evolution term. DEPV argue that finding δ>0 is evidence of anchoring or other primary loan market frictions on historical credit spreads. The third term, γ, captures the unexplained portion of the previous loan spread on $s_{i,t}$. This term is included to control for time-invariant unobserved borrower credit risk characteristics.

We estimate Equation 1 to test for stickiness in both loan and CDS spreads. Table 3 presents our findings (the results of our first-stage spread models can be found in Table B.1 in the appendix). Our sample differs from the sample used by DEPV in two ways. First, unlike DEPV,

[11] Beggs and Graddy (2009) recognize this, stating that their interpretation of the evolution term as evidence of anchoring is based on the "… assumption that no new unobserved quality was introduced between the previous auction and the present auction. It is very unusual to have quality changes between auctions. Paintings are generally very well preserved, and in this dataset it is rare that paintings become known as fakes or that the attribution of the artist changes." (pp. 1030).

we do not drop observations where the change in realized loan spread exceeds 100% since truncation of large changes in spreads biases the coefficient estimate on the spread evolution term upwards.[12] Second, DEPV's sample period ends in 2008, while ours ends in 2016.

As shown in Column 1, for the full sample of loans in our sample, we find that $\hat{\delta} = 0.049$ and statistically significant at the 1% level, indicating that 4.9% of the would-be evolutions are not incorporated in realized spreads. The corresponding estimate in DEPV is 0.22. As shown in the appendix Table B.4, when we follow DEPV's sampling strategy as closely as possible, we find that $\hat{\delta} = 0.20$. The difference between our estimate and theirs is almost entirely due to our inclusion (and their exclusion) of observations where the change in realized spreads exceeds 100%.

We investigate whether CDS spreads are sticky by estimating Equation 1 using CDS spreads instead of loan spreads. For this analysis we estimate the first stage of the CDS spread regression in the same way we estimate the first stage for loan spread regression. Since we are examining CDS spreads on loan dates we include in the first stage regression the characteristics of the loans made on the same date. The results of the first stage estimate are presented in Table B.1 of the appendix. It is interesting to note that we find a significant relation between CDS spreads and several of the loan controls (e.g., secured loan indicator). This suggests that the contract terms on the loan date are informative to market participants.

In Column 2 of Table 3 we present the stickiness tests using CDS spreads. As shown, we find CDS spreads exhibit roughly the same degree of stickiness as loan spreads on loan dates, i.e., $\hat{\delta} = 0.042$ and significant at the 1% level, which indicates that primary loan market frictions such as behavioral biases and bank information monopolies, which are unlikely to influence to pricing

[12] We find that spread changes greater than 100% are not likely data errors since these changes are significantly related to changes in fundamental risk characteristics. Specifically, when we estimate $(s_{i,t} - s_{i,r}) = \alpha + \beta(\hat{s}_{i,t} - \hat{s}_{i,r}) + \varepsilon_{i,t}$ using only spread changes greater than 100%, we find a coefficient estimate of $\beta = 0.42$ with a p-value < 0.001 and $R^2 = 0.25$.

of CDS. As discussed later, we observe stickiness in CDS spreads only facility start dates, suggesting that CDS spreads on these dates are sticky because loan pricing reveals value relevant propriety information on, cannot explain rate stickiness for firms with traded CDS.

In Column 3, we test for stickiness in loan spreads after controlling for CDS spreads on the facility start date. As shown, we find that $\hat{\delta}$ drops to 0.009 and loses significance (*p*-value = 0.536) when CDS spreads are controlled for.[13] Taken together, the evidence in Columns 1 and 3 indicates that inadequate controls for borrower risk characteristics, e.g., omission of proprietary firm-specific information that banks rely on during loan negotiations, lead to upward-biased estimates of δ. In other words, loan spreads appear *stickier* than they truly are due to incomplete or imperfect measurement of borrower risk.

4. The Evolution of Credit Risk and the Quality of Lenders' Private Information

The results in Table 3 suggest that, for firms with traded CDS, spread evolution may capture the effect on spreads of information conveyed by the timing or terms of the loan. In this section, we investigate why spread evolution is positively related to loan spreads. We start by illustrating how time variation in private information concerning borrower quality affects the coefficient estimate on the spread evolution term in Equation 1. In particular, we show that when spread evolution is correlated with the quality of material non-public information that lenders rely upon when making credit decisions, there is an omitted variables problem if Equation 1 is estimated in reduced form. Next, we provide five sets of results consistent with this private information story. First, using Equation 1 and a placebo sample of hypothetical loan dates for our firms with traded CDS, we show that CDS spreads appear to be sticky only on actual loan dates but not on hypothetical event dates, consistent with information conveyed by loan timing or

[13] When we test for the stickiness in loan spreads for the subsample of firms with traded CDS without controlling for CDS spreads, we find that $\hat{\delta} = 0.024$ and statistically significant at the 10% level.

terms driving the CDS stickiness results reported in Column 3 of Table 3. Second, we provide evidence that positive values of the spread evolution term are associated with significant increases in borrower credit risk during the one- to three-year period after the loan date, indicating that spread evolution is a measure of unobserved credit risk.

Third, we examine whether the importance of private information varies with credit spreads and bank lending standards using the methodology proposed by Rajan, Seru, and Vig (2015). Fourth, we document that the coefficient estimate on the spread evolution term is significantly larger where lenders have greatest incentives to invest in private information acquisition. Fifth, we find substantial reductions in the stickiness of loan spreads after initial public offerings and initiation of loan ratings, which reduce the importance of private information in lending decisions by reducing information asymmetries about firm credit quality. Finally, we show significantly greater degree of stickiness for relationship-based revolving lines of credit than for transaction-driven term loans. Moreover, we find no significant stickiness for institutional term loans funded by "arm's length" lenders such as CLOs.

4.1. Does Spread Evolution Reflect Privately Observed Measures of Credit Risk?

To see how spread evolution reflects private information concerning credit risk, assume that loan spreads reflect both privately and publicly observable credit-relevant information. Specifically, assume that the true model of spread determination can be written as:

$$s_{i,t} = \beta \hat{s}_{i,t} + \lambda u_{i,t} + \varepsilon_{i,t}, \tag{2}$$

Here, subscripts *i* and *t* refer to firm and time, respectively, $\hat{s}_{i,t}$ is the estimated loan spread based on observables, and $u_{i,t}$ is the private pricing-relevant information known to the lender but not observable to the econometrician.

Because we do not observe $u_{i,t}$, we cannot estimate Equation 2. Suppose instead we estimate the model in DEPV (denoted earlier as Equation 1):

$$s_{i,t} = \beta\hat{s}_{i,t} + \delta\left(s_{i,r} - \hat{s}_{i,t}\right) + \gamma\left(s_{i,r} - \hat{s}_{i,r}\right) + \varepsilon_{i,t}$$

We can rewrite the predicted spread of the current loan as:

$$\hat{s}_{i,t} = \hat{s}_{i,r} + \Delta c_{i,t} \tag{3}$$

Here, $\Delta c_{i,t}$ is the spread-equivalent of the change in observable firm and loan risk characteristics between the origination dates of the two loans. If we replace $\hat{s}_{i,t}$ with $\hat{s}_{i,r} + \Delta c_{i,t}$, the spread evolution term becomes:

$$(s_{i,r} - \hat{s}_{i,r}) - \Delta c_{i,t} \tag{4}$$

We can thus rewrite the model as:

$$s_{i,t} = \beta\hat{s}_{i,t} + \delta\left(-\Delta c_{i,t}\right) + (\gamma + \delta)\left(s_{i,r} - \hat{s}_{i,r}\right) + \varepsilon_{i,t} \tag{5}$$

Here, finding $\delta > 0$ indicates that, holding current predicted spread constant, firms whose observed credit risk increased since the last loan (i.e., $-\Delta c_{i,t}< 0$ which means $\hat{s}_{i,t} - \hat{s}_{i,r} > 0$) pay lower spreads.[14]

Suppose $\left(s_{i,r} - \hat{s}_{i,r}\right) = u_{i,r}$ so the residual spread associated with the prior loan picks up private information at time r but not at time t. We make this assumption to show the impact of private information. As discussed in the previous section, $u_{i,r}$ potentially captures any omitted observable credit risk measure as well as mis-measurement in the included controls.

DEPV's interpretation of the spread evolution term is based on an assumption that private information doesn't change over time ($u_{i,r} = u_{i,t}$) so that private information (or more generally, omitted credit risk factors) is captured by $\left(s_{i,r} - \hat{s}_{i,r}\right)$. However, if the importance of

---

[14] As shown in Appendix Table B.5, if we estimate Equation 1 by replacing the spread evolution term with $\Delta c_{i,t}$, the coefficient estimate for δ remains the same. The coefficient estimate on lagged residual spread, however, increases by $\hat{\delta}$.

bank screening varies over time with the riskiness of the borrower, so that $u_{i,r} \neq u_{i,t}$, then Equation 1 is mis-specified. To see how this potential misspecification may lead to the appearance of loan rate stickiness, define $u_{i,t} - u_{i,r} = \Delta p_{i,t}$ as the change in the lender's private information set between loan dates. Assuming the importance of screening varies with credit is equivalent to assuming $cov(\Delta c_{i,t}, \Delta p_{i,t}) < 0$, i.e., increases in observed credit risk characteristics imply greater screening and more favorable private information (conditional on loan approval). This implies that $-\Delta c_{i,t}$ is positively correlated with $u_{i,t}$, which biases the estimate of δ upward.

Our empirical analysis below focuses on examining whether $\hat{\delta}$ reflects the effect of private information omitted from the first-stage spread model. The idea is that the importance of private information in determining spreads is a function of the strength of the firm's relationship with the lender and the firm's credit risk. Conditional on obtaining a loan, as observed credit risk increases, reliance on private information also increases. As a result, when spread evolution is negative (predicted spreads are higher than the spread associated with the previous loan) lenders engage in more diligent screening and thus private information affecting the loan is more likely to be favorable. In contrast, when spread evolution is positive (predicted spreads are lower than the spread associated with the previous loan), we expect less screening by relationship lenders and loans spreads to reflect less favorable private information.

We focus in the next sections on how variations in privately observed firm quality can create the appearance of stickiness in the context of the empirical model used by Beggs and Graddy (2009) and DEPV. However, more generally, if variations in the privately observed quality are correlated with market rates or aggregate spreads, the loan rates that are determined in part by private information will appear sticky with respect to market rates.

4.2. *Does Private Information Drive the Stickiness in CDS Spreads?*

Based on the discussion in the previous section, a potential explanation for finding stickiness in CDS spreads on loan dates is that loan contract terms convey heretofore private information that are incorporated into CDS spreads when the loan terms are made public. In addition, firms may time successful loan requests to coincide material new information that affects both CDS spreads and loan spreads.

We test this hypothesis by examining whether CDS spreads exhibit the same degree of stickiness on non-loan dates as they do on loan dates.[15] Specifically, for each firm with traded CDS, we randomly select a trading day in the first year it becomes a CDS reference entity and use this date as well as its 3rd, 6th, 9th, and 12th anniversary as placebo event dates. If the randomly selected date is within (-90, +90) calendar days of a loan date, we select another date in the same year. We set the gap between consecutive event dates to three years because the average time between consecutive loan dates in our sample is three years. Next, we estimate Equation 1 using firms' CDS spreads on placebo event dates. We repeat sampling and estimation 500 times.

Table 4 presents the results of the placebo test. As shown, the average coefficient estimate on the spread evolution term is positive but statistically insignificant. Finding that the relation between spread evolution and the current CDS spread is significant on loan dates but insignificant on non-loan dates is consistent with the private information hypothesis, i.e., loan terms or loan approval conveys material non-public information concerning the borrower's risk characteristics. In contrast to our finding concerning spread evolution, we find that the coefficient estimates on predicted spread and lagged residual spread are positive and similar in magnitude to the coefficient estimates obtained using CDS spreads on loan dates.

[15] Another way is to conduct an event study to test whether CDS spreads respond to loan contract terms. The challenge in conducting this type of test is to determine when information concerning the loan terms are impounded in market prices. As Maskara and Mullineaux (2011) point out, most bank loans are not publicly announced. Moreover, many loans are announced after the facility start date, suggesting that, even for loans that are announced, the information concerning the loan terms may be incorporated into market prices well before the announcement date. Finally, for syndicated loans, pricing and other loan terms may be conveyed to market participants well before the facility start date.

4.3. The Importance of Private Information in Credit Decisions and the Stickiness of Loan Spreads

If stickiness in loan spreads reflects private information that lenders rely upon when negotiation loan terms, we expect the effect of spread evolution on current loan spreads to be largest where information asymmetries about borrower credit quality are most severe and where the lender is most likely to invest in private information acquisition. Past studies provide evidence that asymmetric information problems are more severe and thus reliance on private information in bank lending is greater (i) for unrated firms than for rated firms, e.g., Faulkender and Petersen (2006) and Sufi (2009), (ii) for private firms than for public firms, e.g., Sufi (2007) and Schenone (2010) and (iii) for bank dependent firms than firms that have accessed public bond markets. In addition, evidence suggests that traditional bank lenders are more likely to invest in building and maintaining relationships with their borrowers, and therefore have incentives to invest in gathering private information about their borrowers, than institutional lenders such as collateralized loan obligations and loan mutual funds, which tend to make transaction-based loans.[16] Thus, we expect to find a greatest degree of stickiness in loan spreads when the borrower is unrated, private, bank dependent, and when the loan is funded by bank lenders.

As shown in Table 5, this is exactly what we find. For example, as shown in columns (1) and (2), the estimated coefficient on spread evolution is 0.092 for unrated firms but only 0.022 for rated firms; the difference between the estimates for the two groups is statistically significant at the 1% level. We find a similar difference between bank dependent firms and firms with access to public bond markets. We follow Santos and Winton (2008) and define bank dependent firms as firms that have not accessed the public bond market prior to the loan date.[17] As shown in

[16] For example, Demiroglu and James (2015) argue that institutional investors are less likely to base lending decisions on relationship concerns. Consistent with this argument, they find that institutional lenders are less likely to restructure their loans to distressed borrowers outside of bankruptcy.

[17] We obtain the bond issuance information from Mergent Fixed Income Securities Database (FISD). We then track the history of bond issuances for each firm. For a given loan, the borrower firm is classified as bank dependent if the firm had never issued a public bond prior to loan date. Otherwise, if the firm issued a public bond at least once prior to loan date, we classify it as a firm with access to public bond markets.

columns (3) and (4), the coefficient estimate on spread evolution is 0.079 for bank dependent firms and 0.037 for firms with access to public bond markets; the difference is again significant at the 1% level. We find a similar difference for public versus private firms. Specifically, as shown in columns (5) and (6), the coefficient estimate on spread evolution is 0.149 for private firms and 0.051 for public firms; the difference is again significant at the 1% level. Finally, in columns (7) and (8), we compare the stickiness of loan spreads between bank term loans and institutional term loans. We restrict the comparison to term loans because institutional lenders rarely participate the funding of revolving lines of credit. As shown, we find no evidence of stickiness for institutional term loans, i.e., the coefficient estimate on spread evolution in this sample is *negative* and significant. In contrast, we find a significant degree of stickiness for bank term loans. Overall, the evidence in Table 5 is consistent with the view that stickiness in loan spreads is significantly more pronounced where reliance on private information in lending decisions is greater.

In Appendix C we provide evidence that loan spreads become less sticky once the firm becomes less opaque. Specifically, we investigate changes in the stickiness of loan spreads following two important events that reduce asymmetric information about firm credit quality and expand the firm's loan investor base to relatively less informed lenders: the introduction of loan ratings and public listing of firms' equity. The attractiveness of using panel data is that we can include firm fixed effects to capture potential omitted time-invariant credit risk factors. As shown in Appendix C, we find a significant reduction in stickiness after firms are rated and after firms go public.

4.4. Is Spread Evolution Related to Ex Post Changes in Credit Risk?

In Section 4.1 we show that loan spreads may be positively related to spread evolution because the changes in the importance of bank due diligence are correlated with changes in observable credit risk measures. One way to test whether $cov(\Delta c_{i,t}, \Delta p_{i,t}) < 0$ is to examine the relation between spread evolution (i.e., $-\Delta c_{i,t} = \hat{s}_{i,r} - \hat{s}_{i,t}$) and *future* evolution in credit risk. Specifically, we examine whether spread evolution is positively related to changes in predicted spreads subsequent to time t, controlling for $\hat{s}_{i,t}$. The basic idea is that, in making a loan, the bank will estimate how the credit risk of the borrower is likely to change during the term of the loan. As discussed in the previous section, this estimate is unobservable to the econometrician and thus represents private information that is correlated with the spread evolution term. Our test, therefore, focuses on how predicted spreads evolve over time by comparing $\hat{s}_{i,t}$ to $\hat{s}_{i,t+1}$. This comparison involves essentially asking how the offered loan rate would change given changes in the borrower's financial characteristics after the loan is made.

We implement this test as follows. First, for each year between 1987 and 2016, we estimate a cross-sectional loan spread regression using the set of loans originated in that year and store the yearly coefficient estimates. Next, for each firm that took out a loan in year t, we first predict spreads at time t. We then calculate the predicted spread at time t+1, using firm financial characteristics in year t+1, and coefficient estimates of the spread model as well as the characteristics of the year t loan (that is, we allow firm characteristics to change over time but keep the regression coefficients and loan characteristics constant). Finally, we regress changes in predicted loan spreads (from year t to t+1) on the spread evolution term and predicted spread associated with the time t loan. If spread evolution reflects private information that is negatively related to $\Delta p_{i,t}$, we expect the coefficient estimate on spread evolution to be positive.

Table 6 presents our findings. As shown, we find that, after controlling for $\hat{s}_{i,t}$, the coefficient estimate on the spread evolution term ($s_{i,r} - \hat{s}_{i,t}$) is positive and statistically significant, suggesting that spread evolution might serve as a proxy for unobserved borrower credit quality at time t, consistent with the private information hypothesis.

In Columns 2 and 3 of Panel A, we examine whether the information content of spread evolution is different for revolvers and term loans. As shown, we find that the coefficient estimates on spread evolution are significantly greater for revolving credit agreements than for term loans, suggesting that private information is more important in the lending process for revolving credit agreements.

If spread evolution is correlated with private information obtained by the lender, we expect that the predictive power of spread evolution to vary with our proxies of firm opaqueness. Specifically, we expect the predictive power of spread evolution to be greater for unrated firms than for rated firms and for bank dependent firms than for firms with access to pubic bond markets.[18] This is exactly what we find. As shown in Panel B, we find a positive and significant relation between the future evolution of credit risk and spread evolution only for unrated and bank dependent firms.[19]

4.5. The Importance of Private Information and Credit Market Conditions

In Section 4.1 we argued that variation over time in the importance of private information in lending decisions can give rise to appearance of stickiness in loan rates. Specifically, if reliance on private information is greater when spreads are high or when lending standards are tight than when spreads are low or credit standards are loose, then spread evolution may reflect variation in the importance of private information in lending decisions that is correlated with variations in credit spreads. We examine this issue using a methodology proposed by Rajan, Seru, and Vig (2015). Specifically, they argue that variations in the reliance on private information in lending decisions will result in variations in the explanatory power of hard information based on credit risk measures in cross sectional spread regressions. The private information hypothesis also predicts that the variations in importance of private information over the credit cycle will be

[18] Given the small sample size and the fact that only a few private firms have more than two years of financial information we are unable to estimate the relationship between changes in predicted spreads and spread evolution for private firms.

[19] We also examine the relationship between changes in predicted spreads from time *t* to time *t*+2 and find results similar to those reported in Table 6.

greater for bank dependent/opaque firms than for firms with access to bond markets or rated firms.

Figure 2 provides a preview of our finding. In Figure 2 we plot the R^2s over time from the first stage regression of spreads on borrow and loan characteristics. The top green line plots the R^2s for firms that have issued public bonds and the bottom blue line plots the R^2s for bank dependent firms. The lighter blue shaded areas reflect times when the net proportion of banks tightening credit is less than zero (loose periods) and the darker pink areas are when the net proportion of banks tighting is greater than zero. Consistent with the private information hypothesis, R^2s drop for bank dependent firms during tight credit periods and increase when lending standards are loose. In contrast, except for during the financial crisis (2007—2009), we find very little variation over time in the R^2 for firms with access to public bond markets.

To examine more formally whether lenders reliance on private information varies with credit spreads or credit market conditions we divide our sample into periods of credit contractions and periods of credit expansions. We use two approaches to test the variation in credit market conditions. In the first approach, we partition the sample of loans into "Tight" versus "Loose" credit markets. We rank each year into quartiles with respect to the annual average net percentage of loan officers that report tightening in lending standards. We then classify the lending market in a year as "Tight" or "Loose" market period based on whether the tightening in that year is in highest or lowest quartile, respectively. Table 7, Panel A presents the first-stage loan spread estimation results for the "Tight periods" and "Loose periods". In the first two column, we use a parsimonious model with firm fundemantals to predict loan spreads. In columns (3) and (4), we implement the full model with firm- and loan-level controls. We find that the R^2s of the loan spread regression, based on of the models estimated using publicly available firm- and loan-level information, are lower during the periods of credit contraction. This is consistent with greater reliance by lenders to private information during the periods of tightening in credit standards.

In the second approach, we partition the sample of loans to the periods of "High spreads" and "Low spreads". We first rank each year into quartiles with respect to annual average Moody's Baa corporate bond yield spread. We consider a year as a high spread period if it is in the highest quartile of yield spread. Similarly, low spread periods are the years that fall into lowest quartile of yield spread. Table 7, Panel B presents the first-stage loan spread estimation results for high and low spread periods. In the first two column, we use a parsimonious model with firm fundemantals to predict loan spreads. In columns (3) and (4), we implement the full model with firm- and loan-level controls. In both specifications, we consistently find that high spread periods have lower R^2s. Overall our findings suggest that there is a greater reliance on private information and greater benefits from due diligence efforts during the periods of credit contraction and stringent market conditions.

In Panels C and D of Table 7, we compare the R^2s for rated firms to unrated firms and the R^2 of firms with public debt to bank dependent in loose and tight credit market conditions. Consistent with the pattern reported in Figure 2 we find greater variation in R^2s for opaque firms over the credit cycle than for more transparent firms.

5. Conclusion

We provide evidence that the appearance of stickiness in loan rates relative to changes in market rates arises in part because pricing of bank loans reflects and transmits heretofore credit-relevant private information. Indeed, consistent with the private information story, we find the appearance of stickiness in secondary market CDS spreads. Moreover, when we control for CDS spreads in the loan spread regression, we find no evidence of stickiness. While our results suggest that stickiness arises, in part from an omitted variables problem, we can't rule out the possibility that, for firms without actively traded CDS, stickiness may arise from information frictions or behavioral biases and thus reflects mispricing. Indeed, some of our proxies for opacity and the importance of private information have been used by DEPV, Schenone (2010), and others to identify mispricing arising from informational frictions that insulate relationship lenders from competitive pressures. However, our findings indicate that finding that spreads vary with the path of historical spreads, either in the aggregate or at the firm level, is not definitive evidence of mispricing.

References

Becker, B., Bos, M., & Roszbach, K. (2018). Bad Times, Good Credit. Swedish House of Finance Research Paper No. 15-05.

Becker, B., & Ivashina, V. (2014). Cyclicality of Credit Supply: Firm Level Evidence. *Journal of Monetary Economics, 62*, 76-93.

Beggs, A., & Graddy, K. (2009). Anchoring Effects: Evidence from Art Auctions. *American Economic Review, 99*(3), 1027-1039.

Berg, T., Saunders, A., & Steffen, S. (2016). The Total Cost of Corporate Borrowing in the Loan Market: Don't Ignore the Fees. *Journal of Finance, 71*(3), 1357-1392.

Berger, A. N., & Udell, G. F. (1992). Some Evidence on the Empirical Significance of Credit Rationing. *Journal of Political Economy, 100*(5), 1047-1077.

Berger, A. N., & Udell, G. F. (1995). Relationship Lending and Lines of Credit in Small Firm Finance. *Journal of Business, 68*(3), 351-381.

Berger, A. N., & Udell, G. F. (2002). Small Business Credit Availability and Relationship lending: The importance of bank organisational structure. *Economic Journal, 112*(477), F32-F53.

Berger, A. N., & Udell, G. F. (2004). The Institutional Memory Hypothesis and the Procyclicality of Bank Lending Behavior. *Journal of Financial Intermediation, 13*(4), 458-495.

Bollen, N. P. B., & Pool, V. K. (2009). Do Hedge Fund Managers Misreport Returns? Evidence from the Pooled Distribution. *Journal of Finance, 64*(5), 2257-2288.

Boot, A. W. A. (2000). Relationship Banking: What Do We Know? *Journal of Financial Intermediation, 9*(1), 7-25.

Chava, S., & Roberts, M. R. (2008). How Does Financing Impact Investment? The role of debt covenants. *Journal of Finance, 63*(5), 2085-2121.

Dell'Ariccia, G., & Marquez, R. (2006). Lending Booms and Lending Standards. *Journal of Finance, 61*(5), 2511-2546.

Demiroglu, C., & James, C. (2015). Bank Loans and Troubled Debt Restructurings. *Journal of Financial Economics, 118*(1), 192-210.

Dougal, C., Engelberg, J., Parsons, C. A., & Van Wesep, E. D. (2015). Anchoring on Credit Spreads. *Journal of Finance, 70*(3), 1039-1080.

Faulkender, M., & Petersen, M. A. (2006). Does the Source of Capital Affect Capital Structure? *Review of Financial Studies, 19*(1), 45-79.

Frankel, R., Kothari, S. P., & Weber, J. (2006). Determinants of the Informativeness of Analyst Research. *Journal of Accounting & Economics, 41*(1-2), 29-54.

Fried, J., & Howitt, P. (1980). Credit Rationing and Implicit Contract Theory. *Journal of Money Credit and Banking, 12*(3), 471-487.

Genesove, D., & Mayer, C. (2001). Loss Aversion and Seller Behavior: Evidence from the Housing Market. *Quarterly Journal of Economics, 116*(4), 1233-1260.

Goldfeld, S. (1966). Commercial Bank Behavior and Economic Activity. Amsterdam: North-Holland Press.

Gorton, G. B., & He, P. (2008). Bank Credit Cycles. *Review of Economic Studies, 75*(4), 1181-1214.

Ivashina, V. (2009). Asymmetric Information Effects on Loan Spreads. *Journal of Financial Economics, 92*(2), 300-319.

Jaffee, D. (1971). Credit Rationing and the Commercial Loan Market. New York: Wiley.

Jylha, P. (2011). Hedge Fund Return Misreporting: Incentives and Effects. Working paper.

Keys, B. J., Mukherjee, T., Seru, A., & Vig, V. (2010). Did Securitization Lead to Lax Screening? Evidence from Subprime Loans. *Quarterly Journal of Economics, 125*(1), 307-362.

Loh, R. K., & Stulz, R. M. (2018). Is Sell-Side Research More Valuable in Bad Times? *Journal of Finance, 73*(3), 959-1013.

Maskara, P. K., & Mullineaux, D. J. (2011). Information Asymmetry and Self-selection Bias in Bank Loan Announcement Studies. *Journal of Financial Economics, 101*(3), 684-694.

Mian, A., & Sufi, A. (2009). The Consequences of Mortgage Credit Expansion: Evidence from the Us Mortgage Default Crisis. *Quarterly Journal of Economics, 124*(4), 1449-1496.

Murfin, J., & Petersen, M. (2016). Loans on Sale: Credit Market Seasonality, borrower need, and lender rents. *Journal of Financial Economics, 121*(2), 300-326.

Rajan, U., Seru, A. & Vig,V (2015). The Failure of Models that Predict Failure: Distance, Incentives, and Defaults. *Journal of Financial Economics*, 115 (1), 237-260.

Rodano, G., Serrano-Velarde, N., & Tarantino, E. (2018). Lending Standards over the Credit Cycle. *Review of Financial Studies, 31*(8), 2943-2982.

Santos, J. & Winton, A. (2008). Bank Loans, Bonds and Information Monopolies across the Business Cycle. *Journal of Finance, 63*(3), 1315-1359.

Schenone, C. (2010). Lending Relationships and Information Rents: Do Banks Exploit Their Information Advantages? *Review of Financial Studies, 23*(3), 1149-1199.

Sharpe, S. A. (1990). Asymmetric Information, Bank Lending, and Implicit Contracts - a Stylized Model of Customer Relationships. *Journal of Finance, 45*(4), 1069-1087.

Stein, J. (2002). Infromation Production and Capital Allocation: Decentralized versus Hierarchical firms. *Journal of Finance, 57*(5), 1891-1921.

Sufi, A. (2007). Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans. *Journal of Finance, 62*(2), 629-668.

Sufi, A. (2009). The Real Effects of Debt Certification: Evidence from the Introduction of Bank Loan Ratings. *Review of Financial Studies, 22*(4), 1659-1691.

Wittenberg-Moerman, R. (2008). The Role of Information Asymmetry and Financial Reporting Quality in Debt Trading: Evidence from the Secondary Loan Market. *Journal of Accounting & Economics, 46*(2-3), 240-260.

Figure 1: Stickiness in loan spreads

This figure provides an illustration of stickiness in loan spreads. Abnormal spread is the percentage difference between the actual loan spread and the loan spread predicted based on observable credit risk characteristics. The regression model for predicted spreads is discussed in section 3.2 and the results are presented in Appendix Table B.1. The figure shows the average abnormal spread for two different groups of loans. “Spreads rose” group includes loans where the current predicted loan spread is at least 25% higher than the realized previous loan spread. “Spreads fell” group includes loans where current predicted spread is at least 25% lower than the realized previous loan spread.

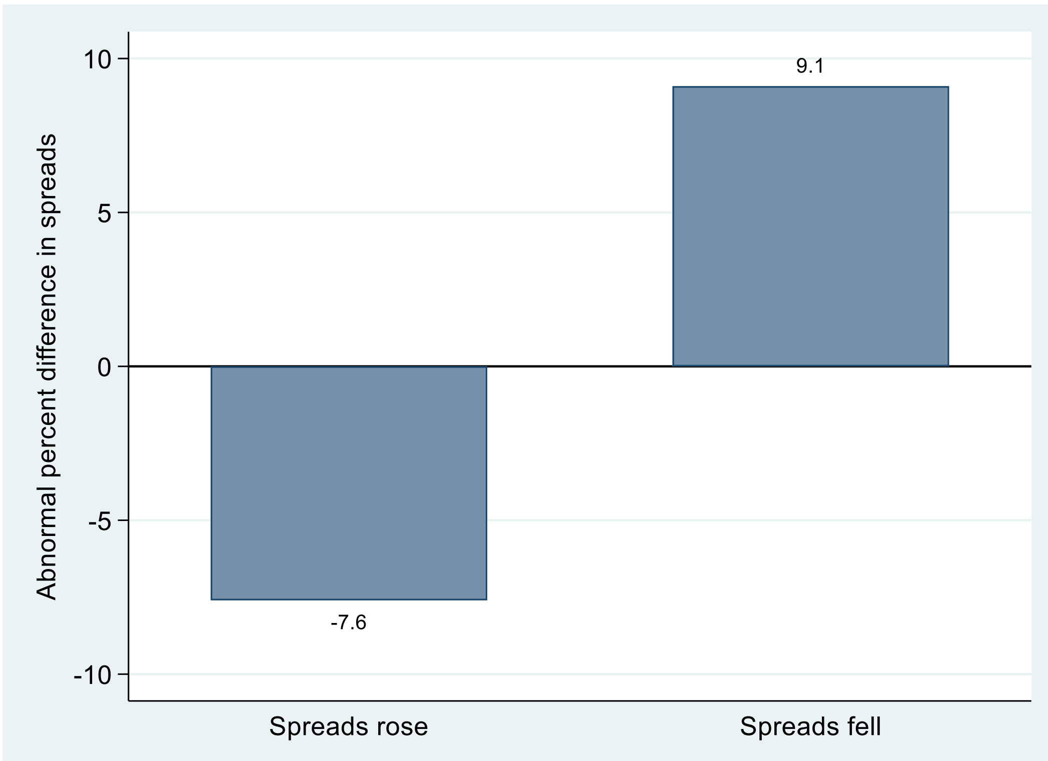

Figure 2: Time-series variation in spread regression R^2s

This figure presents the adjusted R^2s of yearly loan spread regressions, separately for firms with and without publicly traded bonds. The yearly loan spread regression model is discussed in section 3.2. Periods of loosening (tightening) indicate the periods in which net percentage of loan officers reporting tightening lending standard for commercial and industrial loans to large and middle-market firms is negative (positive) according to the Federal Reserve Bank's Senior Loan Officer Opinion Survey on Bank Lending Practices.

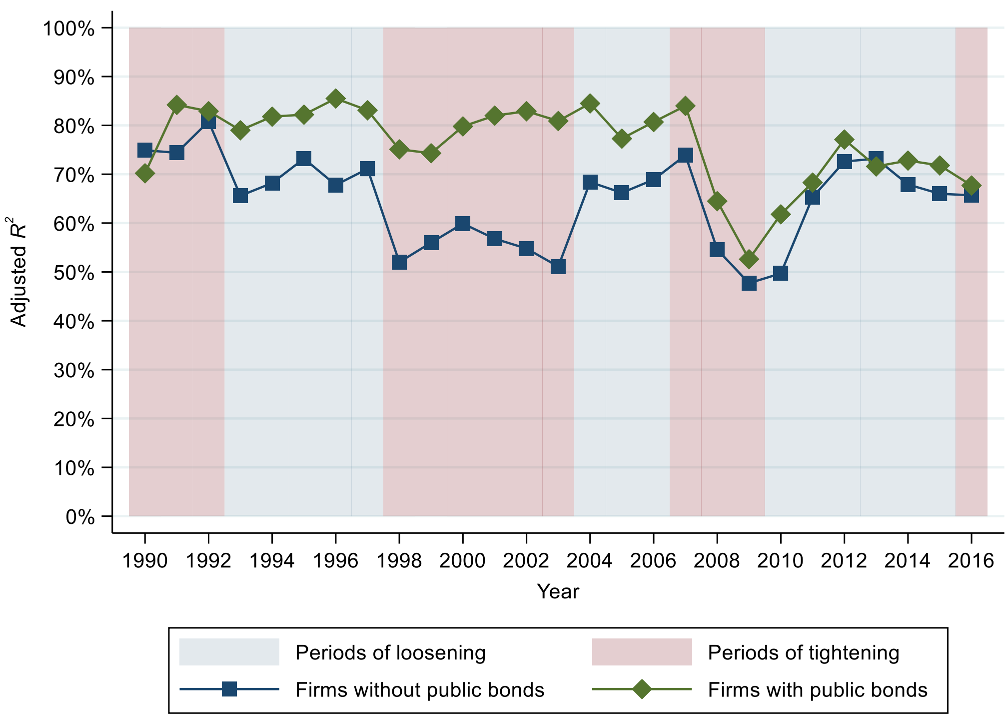

Table 1: Descriptive statistics

This table presents borrower and loan characteristics. The sample period is from 1987 to 2016. For the tests that use CDS information, the sample period is from 2001 to 2016. Appendix D provides variable definitions and sources of data. Panel A shows firm and loan characteristics at loan issuance. Panel B presents the all-in-drawn loan spreads and CDS spreads in basis points for subsamples of loans partitioned with respect to credit ratings and loan types.

Panel A: Firm and loan characteristics at issuance

	All firms			Firms with CDS		
	Mean	Median	*SD*	Mean	Median	*SD*
Firm						
Assets ($mm)	3,793	862	11,858	15,963	7,899	25,565
Sales ($mm)	3,703	871	11,906	14,760	6,626	27,072
Debt-to-assets	0.31	0.28	0.22	0.33	0.29	0.19
Return on assets	0.04	0.04	0.10	0.05	0.05	0.07
Current ratio	1.93	1.69	1.12	1.60	1.48	0.73
Volatility	0.03	0.02	0.02	0.02	0.02	0.01
Loan						
Maturity (months)	52	60	18	57	60	12
Amount ($mm)	387	175	706	1151	800	1319
Spread (bps.)	200	175	129	161	138	120
# of loans		12,938			1,366	
# of firms		3,290			388	

Panel B: Loan and CDS spreads at issuance

	Loan spread (All-in-drawn spread)					CDS spread at the loan issuance date				
	N	Mean	10th	Median	90th	*N*	Mean	10th	Median	90th
By credit rating										
AAA/AA	113	30	15	18	63	35	26	9	17	63
A	730	58	20	37	100	253	66	20	69	100
BBB	1,586	115	38	110	225	525	129	45	125	225
BB	2,361	202	100	175	300	336	200	100	175	300
B	1,530	282	150	250	425	177	299	150	275	450
≤ CCC	110	388	200	350	650	20	494	269	500	813
Not rated	6,508	216	75	200	363	20	201	70	213	300
By loan type										
Revolver	10,064	179	48	160	325	1,133	141	30	125	275
Term loan	2,874	273	125	250	450	233	258	100	225	450
All loans	12,938	200	50	175	350	1,366	161	35	138	300

Table 2: The effect of borrowing histories on current spreads

We estimate the relation between current loan or CDS spread and the change in aggregate spread between two loan dates, using ordinary least squares (OLS) regressions. The sample includes all USD denominated loans of non-financial and non-utility US incorporated firms. In this broader analysis, we do not require firms to have reported financials at the time of loans. Aggregate loan spreads are the average loan spreads, calculated for each year, loan type, and rating group. Δ Aggregate log(Loan spread) is the log difference in aggregate loan spreads between the current loan date and the last time firm borrowed. We similarly calculate aggregate CDS spreads and Δ Aggregate log(CDS spread), using the CDS spreads at loan dates. Heteroscedasticity-robust standard errors are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	Log(Loan spread)	Log(CDS spread)	Log(Loan spread)
Δ Aggregate log(Loan spread)	-0.142***		-0.014
	(0.014)		(0.021)
Δ Aggregate log(CDS spread)		-0.142***	
		(0.030)	
Log(CDS spread)			0.326***
			(0.018)
Constant	5.146***	4.819***	3.243***
	(0.004)	(0.014)	(0.086)
Year/loan type/rating FE	Yes	Yes	Yes
Observations	24,533	2,179	2,179
R-squared	0.431	0.680	0.781

Table 3: Stickiness in loan and CDS spreads

This table presents a formal test of stickiness in both loan and CDS spreads. We estimate the following model:

$$s_{i,t} = \beta \hat{s}_{i,t} + \delta\left(s_{i,r} - \hat{s}_{i,t}\right) + \gamma\left(s_{i,r} - \hat{s}_{i,r}\right) + \epsilon_{i,t}$$

The dependent variable is all-in-drawn loan spread in Columns (1) and (3), and CDS spread in Column (2). Predicted spread, $\hat{s}_{i,t}$, is the predicted value of the current spread. Spread evolution is the difference between realized spread at the inception of the borrower's previous loan and current predicted spread, $s_{i,r} - \hat{s}_{i,t}$. Previous residual is the difference between the actual and predicted spread at the inception of the borrower's previous loan, $s_{i,r} - \hat{s}_{i,r}$. Bootstrapped standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Log(Loan spread)	(2) Log(CDS spread)	(3) Log(Loan spread)
Predicted spread	1.008***	1.006***	0.903***
	(0.005)	(0.008)	(0.020)
Spread evolution	0.049***	0.042***	0.009
	(0.007)	(0.013)	(0.015)
Previous residual	0.155***	0.212***	0.183***
	(0.012)	(0.031)	(0.031)
Log(CDS spread)			0.079***
			(0.013)
Constant	-0.042*	-0.039	0.103*
	(0.024)	(0.042)	(0.058)
Observations	12,938	1,366	1,366
R-squared	0.814	0.910	0.879

Table 4: Placebo test for stickiness in CDS spreads

This table presents the results of placebo test for the stickiness in CDS spreads. We repeat our stickiness test on CDS spreads based on CDS quotes of U.S. firms (with CDS trades and control variables available). We treat a random date for each firm-year as if it were a loan issuance date, and test for CDS spread stickiness. We estimate the predicted CDS spreads in the first stage regressions using all randomly picked quotes of each firm, as if these dates were loan dates (i.e., placebo for loan dates). We use firm-level controls and credit ratings to predict CDS spreads. For the second stage estimations, we require three years to have passed between two randomly chosen CDS quote dates since this is the average time gap between consecutive loans in our sample. We repeat this test for 500 times and report the average of each estimate. Bootstrapped standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) *Mean estimate* Log(CDS spread)
Predicted spread	1.011
	(0.016)
Spread evolution	0.018
	(0.020)
Previous residual	0.177
	(0.037)
Constant	-0.049
	(0.071)
Observations	1,231
R-squared	0.817

Table 5: Private information proxies

This table presents several tests of stickiness using different private information proxies. Columns (1) and (2) show the stickiness for the subsamples of rated and unrated firms. Columns (3) and (4) show the stickiness for the subsamples of firms with and without public bonds prior to loan date. Columns (5) and (6) show the results for the loans of public and private firms. A loan is considered as a private firm loan if the reference entity's stock is not publicly traded at the loan start date. We require both loans in the pair to be issued when reference entity is a public (private) firm to be included in the public (private) firm sample. Columns (7) and (8) show the results for the traditional bank term loans versus institutional term loans. An institutional term loan is defined as the term loan with the market segment of "Institutional." The "Difference" term reports the coefficient estimate for the difference in stickiness between two subsamples in each test (i.e., difference in the spread evolution terms of (2)-(1), (4)-(3), …). Bootstrapped standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rated	Unrated	With bonds	Without bonds	Public firm	Private firm	Institutional term loan	Bank term loan
	Log(Loan s.)	Log(Loan s.)	Log(Loan s.)	Log(Loan s.)	Log(Loan s.)	Log(Loan s.)	Log(Loan s.)	Log(Loan s.)
Predicted spread	0.987***	1.062***	1.000***	1.043***	1.018***	0.944***	0.785***	1.001***
	(0.006)	(0.010)	(0.006)	(0.009)	(0.005)	(0.027)	(0.037)	(0.018)
Spread evolution	0.022***	0.092***	0.037***	0.079***	0.051***	0.149***	-0.047**	0.032*
	(0.008)	(0.010)	(0.008)	(0.011)	(0.007)	(0.031)	(0.023)	(0.019)
Previous residual	0.136***	0.147***	0.132***	0.164***	0.166***	0.206***	0.141***	0.113***
	(0.015)	(0.019)	(0.014)	(0.021)	(0.011)	(0.041)	(0.035)	(0.028)
Constant	0.061**	-0.320***	0.005	-0.229***	-0.090***	0.306**	1.278***	-0.056
	(0.028)	(0.055)	(0.028)	(0.050)	(0.026)	(0.153)	(0.209)	(0.097)
Difference	0.070***		0.042***		0.098***		0.079***	
	(0.013)		(0.014)		(0.032)		(0.029)	
Observations	6,430	6,508	7,544	5,394	14,274	938	1,034	1,840
R-squared	0.863	0.721	0.848	0.735	0.799	0.700	0.544	0.737

Table 6: Ex-post changes in credit risk

This table presents the relation between loan stickiness and changes in predicted spread. Dependent variable "$\hat{s}_{i,t+1}$ - $\hat{s}_{i,t}$" represents the change in predicted spread after current loan, from time *t* to time *t+1*. Predicted spread is the predicted value of loan spread at time *t*. Spread evolution is the difference between realized previous loan spread at time *r* and predicted loan spread at time *t*. Panel A presents the results for all loans as well as revolvers and term loans. Panel B presents the results for the loans of firms with and without credit ratings, and loans of firms with and without public bond issuances in the past, respectively. Bootstrapped standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Loan types

	(1)	(2)	(3)
	All loans	Revolvers	Term loans
Dependent var.:	$\hat{s}_{t+1} - \hat{s}_t$	$\hat{s}_{t+1} - \hat{s}_t$	$\hat{s}_{t+1} - \hat{s}_t$
Predicted spread	-0.007**	-0.007**	-0.028***
	(0.003)	(0.003)	(0.009)
Spread evolution	0.006***	0.007**	-0.002
	(0.002)	(0.003)	(0.006)
Constant	0.058***	0.055***	0.177***
	(0.014)	(0.015)	(0.045)
Observations	11629	9127	2502
R-squared	0.002	0.002	0.005

Panel B: Bank dependence

	(1)	(2)	(3)	(4)
	Rated	Unrated	With bonds	Without bonds
Dependent var.:	$\hat{s}_{t+1} - \hat{s}_t$	$\hat{s}_{t+1} - \hat{s}_t$	$\hat{s}_{t+1} - \hat{s}_t$	$\hat{s}_{t+1} - \hat{s}_t$
Predicted spread	-0.007*	-0.014***	-0.009**	-0.009*
	(0.004)	(0.005)	(0.003)	(0.006)
Spread evolution	-0.001	0.013***	0.003	0.010***
	(0.003)	(0.004)	(0.003)	(0.004)
Constant	0.048***	0.098***	0.058***	0.075***
	(0.017)	(0.027)	(0.016)	(0.027)
Observations	5800	5829	6782	4847
R-squared	0.001	0.005	0.001	0.003

Table 7: Time-series variation in the R^2 of loan spread regressions

This table presents the relation between private information production and credit contraction. Panel A shows the results of first-stage estimations of loan spreads in loose versus tight credit markets. We partition the sample of loans into quartiles with respect to the net percentage of loan officers that report tightening in credit standards at the time of origination. "Loose periods" are the times of credit expansion (first quartile) and "Tight periods" are the times of credit contraction (fourth quartile). Panel B presents the estimation results for the periods of high versus low credit spreads. We rank the 10-year yield spread between Moody's BAA bond and treasury bonds into quartiles to classify "High spreads" and "Low spreads" periods. Panel C shows the adjusted R^2 for the subsamples of loans of rated firms and loans of unrated firms. Panel D shows the adjusted R^2 for the subsamples of loans of firms with public bonds and loans of firms without public bonds. Standard errors clustered by borrower firm are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Tightening in credit standards

	(1) Loose periods Log(Loan spread)	(2) Tight periods Log(Loan spread)	(3) Loose periods Log(Loan spread)	(4) Tight periods Log(Loan spread)
Adjusted R^2	0.625	0.543	0.684	0.622
Firm controls	Y	Y	Y	Y
Loan controls	N	N	Y	Y
Rating FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Loan purpose FE	Y	Y	Y	Y
Lead arranger FE	Y	Y	Y	Y
Observations	7,428	5,439	7,428	5,439

Panel B: Periods of high versus low spread levels

	(1) High spreads Log(Loan spread)	(2) Low spreads Log(Loan spread)	(3) High spreads Log(Loan spread)	(4) Low spreads Log(Loan spread)
Adjusted R^2	0.652	0.571	0.722	0.612
Firm controls	Y	Y	Y	Y
Loan controls	N	N	Y	Y
Rating FE	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y
Loan purpose FE	Y	Y	Y	Y
Lead arranger FE	Y	Y	Y	Y
Observations	7,553	6,387	7,553	6,387

Panel C: Firms with and without credit ratings

	(1)	(2)	(3)	(4)
	Rated firms		Unrated firms	
	Loose periods	Tight periods	Loose periods	Tight periods
	Log(Loan spread)	Log(Loan spread)	Log(Loan spread)	Log(Loan spread)
Adjusted R^2	0.721	0.704	0.645	0.549
Firm controls	Y	Y	Y	Y
Loan controls	N	N	Y	Y
Loan type FE	Y	Y	Y	Y
Loan purpose FE	Y	Y	Y	Y
Lead arranger FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	3,911	1,964	3,517	3,475

Panel D: Firms with and without public bonds

	(1)	(2)	(3)	(4)
	Firms with public bonds		Firms without public bonds	
	Loose periods	Tight periods	Loose periods	Tight periods
	Log(Loan spread)	Log(Loan spread)	Log(Loan spread)	Log(Loan spread)
Adjusted R^2	0.711	0.691	0.658	0.552
Firm controls	Y	Y	Y	Y
Loan controls	N	N	Y	Y
Loan type FE	Y	Y	Y	Y
Loan purpose FE	Y	Y	Y	Y
Lead arranger FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	4,489	2,293	2,939	3,146

Appendix A: Testing for Stickiness in Loan Spreads Using Open-Market Rates

Berger and Udell (1992) focus on whether sticky loan rates reflect credit rationing or inter-temporal interest rate smoothing. Specifically, their stickiness test involves regressing loan spreads on measures of market interest rates as well as controls for loan contract terms, bank characteristics, and macro factors such as the percentage of banks tightening lending standards. The basic idea is that if banks engage in credit rationing or offer implicit interest rate insurance, loan spreads will appear to be sticky with respect to changes in market rates. For example, they interpret a negative relation between loan spreads and duration-matched Treasury rates as evidence that loan spreads are sticky. Berger and Udell (1992) use data on loan spreads from the Federal Reserve's Survey of the Terms of Bank Lending over the period from 1977 through the second quarter of 1988.

We examine whether loan rates are sticky relative to changes in market interest employing a test similar to the one proposed by Berger and Udell (1992). Specifically, we examine the relation between loan spreads and changes in LIBOR. Our specification is similar to the one used by Berger and Udell's except we use LIBOR instead of Treasury rates (since interest rates of a majority of the loans in our sample is tied to LIBOR, not Treasury rates), we use a log-log specification, and we include controls for the financial characteristics of the borrowers as well as additional controls for loan characteristics. The loan and borrower controls are the same as those used in Ivashina (2009) and DEPV in their analyses of loan spreads. In these tests, we restrict the sample to loans of firms with CDS traded to illustrate how additional controls could impact stickiness.

As shown in Column 1 of Table B.2, consistent with Berger and Udell (1992)'s findings, we find a negative and significant relation between loan spreads and LIBOR. The coefficient estimate on LIBOR is -0.31 which implies that, on average, a 10 percent point increase in LIBOR is associated with a 3.1 percent *decrease* in all-in-drawn spreads (AISD). Thus, the total cost of borrowing (the sum of the LIBOR plus AISD) appears sticky in that loan rates rise by less than market rates. In Column 2, we present estimates of the relation between loan spreads and LIBOR including controls for borrower characteristics (something Berger and Udell (1992) were unable to do due limitations on data availability). Note that including borrower controls results in a significant decrease in the stickiness of loan spreads with respect to LIBOR. As shown the coefficient on log LIBOR changes from -0.31 to -0.26 suggesting that omitted credit risk factors contribute to the appearance of stickiness in loan rates. The stickiness is further reduced if we control for CDS spreads.

As Berger and Udell (1992) note, while loan rate stickiness with respect to market rates is consistent with credit rationing, this type of stickiness is also consistent with relationship banks providing implicit interest rate insurance by raising (lowering) rates less than the rise (fall) in market rates or extracting information rents by lowering rates by less than the fall in market rates. A simple way to test whether stickiness in spreads is a unique feature of bank lending is to examine whether we observe a similar degree of stickiness in CDS spreads. For this analysis, we examine the relation between CDS and LIBOR for firms in our Dealscan loan sample. Specifically, for the firms in our sample with traded CDS on loan dates, we use the CDS spreads instead of AISD in the regression of spreads on LIBOR. We use the same borrower and loan controls as before. The results of these regressions are shown in Columns 4 and 5. As shown, CDS spreads also appear to be sticky. Thus, stickiness in credit risk spreads with respect to LIBOR is not a unique feature of the primary loan market and is not necessarily evidence of credit rationing or inter-temporal interest rate smoothing.

Appendix B: Additional Tables

Table B.1: First-stage regression estimates: Controls for firm quality

This table presents the coefficient estimates for our first-stage predictive regressions for loan and CDS spreads. The regressions are run year-by-year to capture time-varying relation between spreads and control variables. "Mean" and "*SD*" columns show the mean and standard deviation for the coefficient estimates, standard errors, number of observations, and adjusted R-squared of these regressions. Left and right panels present the results for the first-stage estimations for loan and CDS spreads, respectively. Dependent variables are logarithm of all-in-drawn loan spread and logarithm of CDS spread for left and right panels, respectively. Commercial p. rating is an indicator that equals to one if reference firm has a commercial paper rating and zero otherwise. Debt-to-assets is the ratio of total book debt to total assets. Current ratio is the ratio of current assets to current liabilities. ROA is the ratio of net income to total assets. Return volatility is the standard deviation of stock returns in the quarter prior to loan start date. Lead mkt. share is the market share of the lead arranger in the syndicated loan market. Log(Amount) is the logarithm of loan amount. Maturity is the maturity of loan in months. # of lenders is the number of lenders in the loan syndicate. Secured is an indicator that equals one if the loan is secured, and zero otherwise. Covenants is an indicator that equals one if the loan has financial covenants, and zero otherwise. Performance pricing is an indicator that equals one if the loan has performance pricing feature, and zero otherwise. Prime base rate is an indicator that equals one if the base rate of the loan is prime, and zero otherwise. All estimations include fixed effects for firm S&P credit ratings, loan type, loan purpose, and lead arranger.

	Log(Loan spread)				Log(CDS spread)			
	Coefficients		Standard errors		Coefficients		Standard errors	
	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*
Commercial p. rating	-0.07	0.15	0.09	0.04	-0.15	0.25	0.16	0.07
Log(Sales)	-0.03	0.03	0.03	0.01	0.02	0.16	0.09	0.04
Log(Assets)	-0.02	0.05	0.03	0.01	-0.02	0.15	0.10	0.04
Debt-to-assets	0.30	0.17	0.10	0.05	0.52	0.52	0.37	0.18
Current ratio	-0.02	0.03	0.02	0.01	0.00	0.10	0.08	0.03
ROA	-0.49	0.33	0.18	0.09	-1.44	1.63	0.91	0.42
Return volatility	3.43	2.06	1.13	0.38	19.62	11.62	5.85	2.15
Lead mkt. share	-0.09	1.06	0.59	0.90	-0.04	0.40	0.46	1.15
Log(Amount)	-0.04	0.03	0.02	0.01	0.01	0.07	0.06	0.02
Maturity	0.000	0.002	0.001	0.000	0.000	0.006	0.004	0.002
# of lenders	0.001	0.006	0.003	0.002	-0.001	0.013	0.008	0.004
Secured	0.29	0.12	0.04	0.02	0.24	0.24	0.15	0.05
Covenants	-0.05	0.16	0.09	0.19	-0.02	0.20	0.14	0.06
Performance pricing	-0.09	0.16	0.07	0.09	-0.07	0.15	0.13	0.05
Prime base rate	0.40	0.34	0.13	0.09	0.10	0.37	0.62	0.11
	Observations		Adj. R^2		Observations		Adj. R^2	
	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*
	917	339	0.70	0.08	184	88	0.84	0.05

Table B.2: Sensitivity of spreads to LIBOR

This table presents the sensitivity of loan and CDS spreads to movements in LIBOR. All variables are described in Appendix D. Heteroscedasticity-robust standard errors clustered by year are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Log(Loan spread)	(2) Log(Loan spread)	(3) Log(Loan spread)	(4) Log(CDS spread)	(5) Log(CDS spread)
Log(LIBOR 3m)	-0.309***	-0.260***	-0.212***	-0.267***	-0.191***
	(0.039)	(0.026)	(0.024)	(0.058)	(0.032)
Log(CDS spread)			0.252***		
			(0.024)		
Commercial p. rating		0.030	0.046		-0.061
		(0.032)	(0.022)		(0.063)
Log(Sales)		-0.019	-0.024		0.021
		(0.017)	(0.013)		(0.023)
Log(Assets)		0.033*	0.037***		-0.013
		(0.011)	(0.008)		(0.038)
Debt-to-assets		0.098	0.008		0.357**
		(0.077)	(0.065)		(0.104)
Current ratio		0.010	0.015		-0.020
		(0.015)	(0.015)		(0.023)
ROA		-0.885***	-0.625***		-1.032**
		(0.201)	(0.134)		(0.323)
Return volatility		9.507***	3.785**		22.714***
		(0.986)	(1.123)		(2.475)
Lead mkt. share	0.035	0.012	-0.003	0.098	0.060
	(0.026)	(0.019)	(0.016)	(0.046)	(0.029)
Log(Amount)	-0.129***	-0.045***	-0.050***	-0.118***	0.020
	(0.015)	(0.011)	(0.012)	(0.023)	(0.018)
Maturity	-0.004*	-0.003*	-0.002*	-0.005	-0.002
	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)
# of lenders	-0.002	-0.004**	-0.004**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Secured	0.756***	0.303***	0.247***	1.152***	0.222***
	(0.059)	(0.050)	(0.041)	(0.048)	(0.054)
Covenants	0.088*	0.013	0.000	0.126	0.052
	(0.040)	(0.019)	(0.017)	(0.074)	(0.035)
Performance pricing	-0.051	-0.015	0.001	-0.173**	-0.066
	(0.043)	(0.034)	(0.029)	(0.053)	(0.038)
Prime base rate	1.494***	1.667***	1.672***	-0.266	-0.022
	(0.252)	(0.258)	(0.235)	(0.299)	(0.196)
Rating FE	N	Y	Y	N	Y
Loan type FE	Y	Y	Y	Y	Y
Loan purpose FE	Y	Y	Y	Y	Y
Lead arranger FE	Y	Y	Y	Y	Y
Observations	2,946	2,946	2,946	2,946	2,946
Adjusted R^2	0.624	0.787	0.810	0.519	0.785

Table B.3: Replication of Dougal et al. (2015) Table II

This table presents our replication of Dougal et al. (2015) Table II results for the impact of borrowing histories on current loan spreads. Loan spreads rose is a dummy variable that equals one if aggregate spreads have risen more than 25% since the last time the firm has borrowed, and zero otherwise. Loan spreads fell is a dummy variable that equals one if aggregate spreads have fallen more than 25% since the last time the firm has borrowed, and zero otherwise. Δ Agg. log(Loan spread) is the log difference in aggregate spreads between the current loan date and the last time firm borrowed. Panel A presents Dougal et al (2015) findings. Panel B presents our replication. Heteroskedasticity-robust standard errors are reported in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Dougal et al. (2015) Table II

	(1) Log(Loan spread)	(2) Log(Loan spread)
Loan spreads rose	-0.11***	
	(0.01)	
Loan spreads fell	0.11***	
	(0.01)	
Δ Agg. log(Loan spread)		-0.21***
		(0.02)
Constant	5.04***	5.05***
	(0.01)	(0.00)
Year/loan type/rating FE	Yes	Yes
Observations	15,536	14,437
R-squared	0.538	0.539

Panel B: Our replication

	(1) Log(Loan spread)	(2) Log(Loan spread)
Loan spreads rose	-0.05***	
	(0.02)	
Loan spreads fell	0.14***	
	(0.02)	
Δ Agg. log(Loan spread)		-0.18***
		(0.02)
Constant	5.03***	5.03***
	(0.01)	(0.01)
Year/loan type/rating FE	Yes	Yes
Observations	16,714	16,714
R-squared	0.407	0.408

Table B.4: Replication of Dougal et al. (2015) Table V

This table presents our replication of Dougal et al. (2015) Table V results for the anchoring in loan spreads. Following Dougal et al. (2015), regressions are run for repeat loans from 1987 to 2008, and for the subsamples of *Revolvers* ("Revolver <1 year," "Revolver ≥1 year,", and "Term/Revolver") and *Term loans*. The dependent variable is all-in-drawn loan spread. Predicted spread is the predicted value of loan spread at time *t*. Spread evolution is the difference between realized loan spread at time *r* and predicted loan spread at time *t*. Previous residual is the residual value from the first-stage regression for the loan at time *r*. Panel A shows the "Table V" of Dougal et al. (2015). In Panel B, we present our replication of this table, using the same firm- and loan-level controls in both the first and second stages. This replication is only possible if the repeat loans with "Δlog(*loan spread*$_{i,t}$) > 100%" are excluded from the sample. In Panel C, we present the replication results if we exclude non-US firms, non-USD loans, and short-term lines of credit from the sample. In Panel D, we present the full sample results without excluding the repeat loans with "Δlog(*loan spread*$_{i,t}$) > 100%." Bootstrapped standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Dougal et al. (2015), Table V

	(1) All Log(Loan spread)	(2) Revolver Log(Loan spread)	(3) Term loan Log(Loan spread)
Predicted spread	0.96***	0.98***	0.79***
	(0.01)	(0.01)	(0.03)
Spread evolution	0.22***	0.22***	0.16***
	(0.01)	(0.01)	(0.04)
Previous residual	0.07***	0.06***	0.10***
	(0.01)	(0.02)	(0.04)
Constant	0.17***	0.08***	1.10***
	(0.04)	(0.04)	(0.18)
Observations	8,525	6,935	1,590
R-squared	0.688	0.698	0.447

Panel B: Replication

	(1) All Log(Loan spread)	(2) Revolver Log(Loan spread)	(3) Term loan Log(Loan spread)
Predicted spread	1.04***	1.05***	1.01***
	(0.00)	(0.01)	(0.02)
Spread evolution	0.20***	0.22***	0.14***
	(0.01)	(0.01)	(0.03)
Previous residual	0.13***	0.12***	0.16***
	(0.01)	(0.01)	(0.03)
Constant	-0.26***	-0.31***	-0.12
	(0.02)	(0.03)	(0.09)
Observations	10,087	8,017	2,070
R-squared	0.828	0.832	0.739

Panel C: Replication using only US firms, USD loans, and long-term lines of credit

	(1) All Log(Loan spread)	(2) Revolver Log(Loan spread)	(3) Term loan Log(Loan spread)
Predicted spread	1.03***	1.04***	1.00***
	(0.00)	(0.01)	(0.02)
Spread evolution	0.18***	0.19***	0.11***
	(0.01)	(0.01)	(0.03)
Previous residual	0.15***	0.15***	0.14***
	(0.01)	(0.02)	(0.03)
Constant	-0.18***	-0.21***	-0.05
	(0.02)	(0.03)	(0.10)
Observations	8,301	6,542	1,759
R-squared	0.836	0.838	0.717

Panel D: Full sample results

	(1) All Log(Loan spread)	(2) Revolver Log(Loan spread)	(3) Term loan Log(Loan spread)
Predicted spread	1.01***	1.02***	0.96***
	(0.01)	(0.01)	(0.02)
Spread evolution	0.05***	0.07***	-0.01
	(0.01)	(0.01)	(0.02)
Previous residual	0.15***	0.15***	0.13***
	(0.01)	(0.02)	(0.03)
Constant	-0.06**	-0.11***	0.23**
	(0.03)	(0.03)	(0.11)
Observations	8,980	7,084	1,896
R-squared	0.817	0.818	0.711

Table B.5: Alternative model

This table presents the stickiness in loan spreads for alternative specification experiment where we define spread evolution terms differently. The dependent variable is all-in-drawn loan spread. Predicted spread is the predicted value of loan spread at time *t*. Spread evolution is the difference between realized loan spread at time *r* and predicted loan spread at time *t*. Previous residual is the residual value from the first-stage regression for the loan at time *r*. In Panel A, we present the stickiness results with the current baseline model. In Panel B, we present the results with the alternative model. Bootstrapped standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline model:

$$s_{i,t} = \beta \hat{s}_{i,t} + \delta\left(s_{i,r} - \hat{s}_{i,t}\right) + \gamma\left(s_{i,r} - \hat{s}_{i,r}\right) + \epsilon_{i,t}$$

	Log(Loan Spread)		
	(1)	(2)	(3)
	All	Revolver	Term loan
Predicted spread $[\hat{s}_{i,t}]$	1.008***	1.014***	0.994***
	(0.005)	(0.005)	(0.016)
Spread evolution $[s_{i,r} - \hat{s}_{i,t}]$	0.049***	0.059***	0.018
	(0.007)	(0.007)	(0.016)
Previous residual $[s_{i,r} - \hat{s}_{i,r}]$	0.155***	0.158***	0.133***
	(0.012)	(0.014)	(0.023)
Constant	-0.042*	-0.066**	0.023
	(0.024)	(0.028)	(0.088)
Observations	12,938	10,064	2,874
R-squared	0.814	0.812	0.720

Panel B: Alternative model:

$$s_{i,t} = \beta \hat{s}_{i,t} + \delta\left(\hat{s}_{i,r} - \hat{s}_{i,t}\right) + (\gamma + \delta)\left(s_{i,r} - \hat{s}_{i,r}\right) + \epsilon_{i,t}$$

	Log(Loan Spread)		
	(1)	(2)	(3)
	All	Revolver	Term loan
Predicted spread $[\hat{s}_{i,t}]$	1.008***	1.014***	0.994***
	(0.005)	(0.005)	(0.016)
Spread evolution $[\hat{s}_{i,r} - \hat{s}_{i,t}]$	0.049***	0.059***	0.018
	(0.006)	(0.007)	(0.016)
Previous residual $[s_{i,r} - \hat{s}_{i,r}]$	0.204***	0.216***	0.150***
	(0.011)	(0.013)	(0.021)
Constant	-0.042*	-0.066**	0.023
	(0.025)	(0.027)	(0.087)
Observations	12,938	10,064	2,874
R-squared	0.814	0.812	0.720

Appendix C: Does Stickiness Change with Changes in Firms' Information Environment?

In this appendix we examine, for a given firm, whether loan spreads become less sticky once the firm becomes less opaque. Specifically, we investigate changes in the stickiness of loan spreads following two important events that reduce asymmetric information about firm credit quality and expand the firm's loan investor base to relatively less informed lenders: the introduction of loan ratings and public listing of firms' equity. The attractiveness of using panel data is that we can include firm fixed effects to capture potential omitted time-invariant credit risk factors.

C.1 Introduction of Loan Ratings

Loan ratings were introduced by S&P in 1995. Evidence suggests that they help expand a loan's initial investor base (Sufi, 2007, 2009) and enhance secondary market liquidity (Wittenberg-Moerman, 2008) by revealing information about borrower credit quality and thereby reducing asymmetric information. As a result, we expect the importance of private information when determining loan pricing to decrease after a firm's loans are rated, which, in turn, will decrease the stickiness in loan spreads.

In Panel A of Table C.1, we examine whether the stickiness in loan spreads changes after the introduction of loan ratings. For each firm, we consider the date that any of its loans receives a rating from S&P for the first time (as recorded by S&P's RatingsXpress database) as the loan rating inception date. To be included in our sample, a firm must have at least two loans before and two loans after this date which allows us estimate Equation 1 before and after the firm becomes rated.

As shown in Column 1 and 2, the coefficient estimate on spread evolution is 0.060 before rating inception and 0.022 after (significant at the 1% and 5% level, respectively), suggesting that loan spreads become less sticky in the presence of a loan rating. To formally test the change in stickiness, we pool loans made before and after the introduction of loan ratings, and estimate a spread model including interaction terms between the indicator *Post rating* and all the regressors (including the intercept) in the first two columns. As shown in Column 3, the coefficient estimate on *Post rating*Spread evolution* is -0.065 (significant at the 1% level), which indicates a significant reduction in stickiness after the inception of loan ratings. In addition, we find that the sum of the coefficient estimates on *Spread evolution* and *Post loan rating x Spread evolution* is indistinguishable from zero, suggesting that loan spreads do not exhibit any stickiness in the presence of loan ratings. Finally, as shown in Column 4, we obtain similar results when we include firm fixed effects. Firm fixed effects allow us to examine within firm changes in stickiness.

C.2 Public Listing of Firm's Equity

Our second test of how changes in a firm's information environment affect loan rate stickiness is in the spirt of Schenone (2010). Her analysis focuses on how information asymmetries affect the ability of relationship lenders to extract rents from their borrowers. She employs an identification strategy based on the notion that large information shocks that increase competition among banks reduces relationship lender's information monopoly. A borrower's initial public offering (IPO), she argues, is large information releasing event that reduces the information asymmetries. We adopt her identification strategy and examine how going public affects loan rate stickiness. In particular, we conjecture that public trading of firms' stocks will make both the syndication process more efficient and trading more liquid, as information about firms' creditworthiness will be readily available and efficiently reflected in their stock prices. As a result, we expect loan rate stickiness to decrease after IPOs.

For the IPO analysis we use the same methodology we used in the loan rating analysis. Specifically, we restrict the estimation sample to firms with multiple loans both before and after the IPO. Because we have limited data on firm financials for the years before IPO, our pre-IPO sample is very small, which reduces the power of our tests. We therefore consider the IPO analysis as a robustness check. As shown in Column 1 and 2, of Panel B of Table C.1 the coefficient estimate on spread evolution is 0.231 before firms publicly list their shares and only 0.055 after (both significant at the 1% level), suggesting that loan spreads become substantially less sticky after going public. We formally test this in Column 3, using a fully interacted model, and find that the reduction in stickiness is 0.176 (significant at the 5% level), indicating a 76% reduction relative to the stickiness levels in the pre-IPO period.

Table C.1: Shocks to private information

This table presents the changes in loan stickiness after the introduction of shocks to firm's private information environment. We use two proxies for private information. Panel A presents the results where the sample is first split into the loans that were issued before and after the firm received a loan rating. We require both loans in the loan pair to be issued before the loan rating to consider them in the sample of pre-loan rating. And, both loans in the loan pair are required to be issued after the loan rating to be considered in the post-loan rating sample. Panel B presents the stickiness results before and after the public listing of firms' stock. Similarly, we require both loans in the loan pair to be issued before and after public listing to be included in the pre- and post-public listing samples, respectively. Private firm years in addition to public firm years are included in these tests. Bootstrapped standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Introduction of loan ratings

	(1)	(2)	(3)	(4)
	Pre-rating	Post-rating	All eventually rated	All eventually rated
	Log(Loan spread)	Log(Loan spread)	Log(Loan spread)	Log(Loan spread)
Predicted spread	1.033***	0.968***	1.033***	1.021***
	(0.011)	(0.009)	(0.011)	(0.018)
Spread evolution	0.060***	0.022**	0.060***	0.050***
	(0.015)	(0.011)	(0.016)	(0.017)
Previous residual	0.162***	0.158***	0.162***	0.038
	(0.027)	(0.021)	(0.026)	(0.029)
Predicted spread x Post rating			-0.065***	-0.119***
			(0.014)	(0.021)
Evolution x Post rating			-0.038**	-0.063***
			(0.019)	(0.020)
Previous residual x Post rating			-0.003	0.001
			(0.033)	(0.038)
Post rating			-0.003	0.001
			(0.033)	(0.038)
Constant	-0.166***	0.177***	-0.166***	-0.121
	(0.057)	(0.049)	(0.057)	(0.090)
Firm FE	N	N	N	Y
Observations	2,304	3,950	6,254	6,254
R-squared	0.811	0.830	0.832	0.876

Panel B: Public listing

	(1) Pre-public listing Log(Loan spread)	(2) Post-public listing Log(Loan spread)	(3) All eventually listed Log(Loan spread)	(4) All eventually listed Log(Loan spread)
Predicted spread	0.954***	1.014***	0.954***	0.813***
	(0.061)	(0.005)	(0.061)	(0.096)
Spread evolution	0.231***	0.055***	0.231***	0.116
	(0.078)	(0.006)	(0.077)	(0.093)
Previous residual	0.146*	0.161***	0.146*	0.003
	(0.083)	(0.012)	(0.085)	(0.107)
Predicted spread x Post public			0.060	0.165*
			(0.061)	(0.096)
Evolution x Post public			-0.176**	-0.091
			(0.077)	(0.093)
Previous residual x Post public			0.015	-0.052
			(0.086)	(0.108)
Post public listing			-0.306	-0.914*
			(0.342)	(0.531)
Constant	0.233	-0.073***	0.233	1.020*
	(0.338)	(0.024)	(0.341)	(0.529)
Firm FE	N	N	N	Y
Observations	156	15,003	15,159	15,159
R-squared	0.681	0.802	0.802	0.870

Appendix D: Variable Descriptions

Variable	Type	Description	Source
Dependent variables			
Loan spread	Basis points	All-in-drawn spread over LIBOR.	Dealscan
CDS spread	Basis points	CDS spread at the loan start date.	Markit
Firm-level variables			
Commercial p. rating	Yes/No	An indicator that equals one if reference firm has a commercial paper rating outstanding, and zero otherwise.	Compustat
Sales	$mm	Firm's total revenue at the latest fiscal period that ended prior to loan start date.	Compustat
Assets	$mm	Firm's total assets at the latest fiscal period that ended prior to loan start date.	Compustat
Debt-to-assets	Ratio	The ratio of total book debt to total assets.	Compustat
Current ratio	Ratio	The ratio of current assets to current liabilities.	Compustat
ROA	Ratio	The ratio of net income to total assets.	Compustat
Return volatility	Decimal	The standard deviation of stock returns in the quarter prior to loan start date.	CRSP
Loan-level variables			
Lead mkt. share	Decimal	The market share of the lead arranger in the syndicated loan market.	Dealscan
Amount	$	Loan amount.	Dealscan
Maturity	Months	Maturity of the loan.	Dealscan
# of lenders	Decimal	Number of lenders in the loan syndicate.	Dealscan
Secured	Yes/No	An indicator that equals one if the loan is secured, and zero otherwise.	Dealscan
Covenants	Yes/No	An indicator that equals one if the loan has financial covenants, and zero otherwise.	Dealscan
Performance pricing	Yes/No	An indicator that equals one if the loan has performance pricing feature, and zero otherwise.	Dealscan
Prime base rate	Yes/No	An indicator that equals one if the base rate of the loan is prime, and zero otherwise.	Dealscan
Group indicators			
Revolver	Yes/No	Equals one if the loan type is revolving line of credit.	Dealscan
Term loan	Yes/No	Equals one if the loan type is term loan.	Dealscan
Rated	Yes/No	Equals one if the firm has credit rating at the loan start date.	Compustat
Institutional term loan	Yes/No	Equals one if the market segment of the term loan is "Institutional," and zero otherwise.	Dealscan
Private firm	Yes/No	Equals one if the reference firm's equity is not publicly traded, and zero otherwise.	CRSP
Post-loan rating	Yes/No	Equals one if both loans in the pair are issued after the firm received a loan rating. Equals zero if both loans in the pair are issued before the firm received a loan rating.	S&P RatingsXpress
Post-public listing	Yes/No	Equals one if both loans in the pair are issued after the firm is publicly listed. Equals zero if both loans in the pair are issued before the firm is publicly listed.	CRSP
Loose/Tight markets	Yes/No	Determined by the net % of loan officers that report tightening in credit standards at the time of loan origination. The credit market is “Tight” if tightening is in highest quartile, and “Loose” if tightening is in lowest quartile.	FED
Low/High spreads	Yes/No	Determined by the yield spread of Moody’s Baa rated corporate bonds. The credit market has “High” spread level if yield spreads are in the highest quartile, and “Low” spread level if yield spreads are in the lowest quartile.	FED
With/Without bond	Yes/No	The borrower firm is classified as “With bond” if it had issued a public bond prior to loan start date, and “Without bond” otherwise.	Mergent FISD