Moral Hazard, Bank Monitoring, and Bond Spreads

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Abstract

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Keywords: Banking Relationships, Bank Loans, Corporate Debt, Yield Spreads, Bank Cross-Monitoring, CDS Spreads.

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Abstract

We test the hypothesis that bank monitoring causes lower yields on public bonds. We find that firms with a banking relationship have 15 basis points lower yield spreads on their public debt, similar in magnitude to a two-notch rating upgrade, or a standard deviation increase in profitability. The effect of a banking relationship is larger for firms with a dispersed bond ownership, junk debt, and no credit default swaps. Our results are robust to IV estimation and a quasi-natural experiment. In the market for information production, it appears that bank monitoring cross-subsidizes credit risk, directly benefiting bondholders.

I. Introduction

We test whether bondholders benefit directly from bank monitoring. When incentives are aligned, bondholders can free-ride on a banks' monitoring efforts, leading to lower required bond yields. Alternatively, banks may leverage their private information to the detriment of bondholders, especially for firms approaching financial distress. These opposing effects may cancel each other out or become less relevant for large syndicated loans with bond-like features. As a result, the net effect of bank monitoring on bondholder required returns is, ultimately, an empirical question.

We find the data tend to support the free-riding hypothesis. Firms with a bank relationship have a 15 bps lower yield spread on their public debt relative to firms without a bank relationship. This effect is similar in magnitude to a two-notch credit rating upgrade or roughly a standard deviation increase in profitability.[1]

Theoretically, the net effect of bank monitoring on the cost of public debt is ambiguous. Bank monitoring could lead to lower yield spreads as Fama (1985) argues, since a loan renewal implies that bondholders need not undertake duplicate evaluation of borrowers' creditworthiness and subsequent monitoring.[2] A loan renewal is a credible signal given banks' large financial stakes in their borrowers and private information from prior monitoring (Boot (2000)). In addition, bondholders might delegate monitoring to banks because banks have lower monitoring costs (Diamond (1984), Park (2000)). Under this free-riding hypothesis, cost savings from more efficient monitoring should result in lower required bond yields.

On the other hand, bank monitoring could lead to higher bond yields. Under the "bank-predation" hypothesis, banks could extract rents from the firm by using the information from prior monitoring to exert undue influence over management, and secure benefits to the detriment of bondholders (see e.g., Rajan (1992), Sharpe (1990)).[3] During loan renegotiations, for example, banks may pressure management to convert an existing unsecured

[1] A one notch is the difference between two consecutive ratings – the difference between BBB- and BBB.
[2] Gustafson et al. (2016) show that banks monitor approximately 50% of syndicated loans on a monthly basis.
[3] Mester et al. (2006) show that banks, unlike bondholders, have access to borrower transaction accounts, which they use to monitor borrowers.

credit line to a secured credit line, effectively subordinating unsecured bondholders. Such outcomes are especially common for firms in financial distress (Jenkins and Smith (2014)). Rational bondholders will anticipate the banks' ability to benefit at their expense, leading to higher bond yields.

Finally, the "syndication" hypothesis stipulates that a banking relationship could have little practical effect on bond yields. Syndicated loans are a hybrid of bilateral loans and public debt. As the number of participating lenders increases, moral hazard problems drive syndicated loans to suffer the same coordination and free-rider problems as public bonds (Chemmanur and Fulghieri (1994), Sufi (2007), Ivashina (2009)). The existence of credit risk transfer mechanisms, via loan sales or the purchase of credit default swaps (CDSs), can also reduce a bank's incentive to monitor, because the bank doesn't appropriate the full return from monitoring.[4] Consequently, bank monitoring may have no real impact on bond yields, all else equal.[5] Given these conflicting predictions, whether bondholders are positively or negatively affected by bank monitoring is an empirical question.

It is challenging to measure the causal effect of bank relationships on debt spreads because many variables that drive bank relationships also explain variation in spreads. For example, if lenders form relationships with better quality firms, it is not surprising that such firms have lower yield spreads. A bank relationship is endogenous to the leverage decision. Since leverage is so persistent (Lemmon et al. (2008)), we begin by using firm-fixed effects to mitigate endogeneity concerns. However, given that time-varying unobservables can simultaneously affect relationship formation and bond yields, even firm-fixed effects are not sufficient.

To help identify a causal relationship, we also employ a quasi-natural experiment focused on an exogenous decline in the asset values of energy firms in 2014. Between July and December 2014, an unexpected supply shock to crude oil caused a 44% reduction in oil prices and a precipitous decline in the financial health of many energy companies. If banking

[4] Parlour and Plantin (2008) show that when the gains from selling loans are large the only equilibrium is one without information production on borrowers. We assume that loan buyers and CDS sellers do not monitor, or have a weaker monitoring ability than the bank.

[5] It is possible that loan syndication and/or credit risk transfer reduce, rather than eliminate, spillover effects of a banking relationship on bond yields. The syndication hypothesis can be interpreted as stipulating that the effect of banking relationships on bond yields will be so weak that, in the data, it is indistinguishable from zero.

relationships are valuable to bondholders, we expect oil firms with a banking relationship to experience a smaller decrease in the value of their outstanding bonds than oil firms without banking relationships. On the other hand, firms in financial distress are more likely to face information hold-up problems from their banks. Thus, the exogenous negative shock to assets values is well-suited to test whether the bank predation hypothesis prevails during periods of financial distress. To test these hypotheses, we construct a triple-difference estimator by comparing firms before and after the shock, who are in or out of the energy industry, and who have or don't have a banking relationship. Our findings suggest that banking relationships are especially valuable when firms are under economic stress and the marginal benefit of monitoring is high. We find no evidence that banks extract rents from energy firms in distress.

In addition to the quasi-natural experiment, we use two instruments for bank relationships. Our first instrument is the geographical distance between a firm and its lender. A firm with headquarters close to its bank is more likely to have a relationship, because the bank can easily gather information on the firm, facilitating relationship development. For example, a nearby bank may have more intangible information about the firm, such as the competence and character of its management. Our second instrument is the median amount of bank branch deposits in the county in which a firm is headquartered. Banks with high deposit financing are more likely to extend loans, especially to firms located nearby (Ivashina and Scharfstein (2010)). These instruments are both credibly exogenous because neither is a choice variable that bondholders use to set yield spreads, and both are geographic constraints not chosen by the firm, at least in any practical sense. Our IV results are qualitatively similar, suggesting that our results are unlikely to stem from reverse causality or an omitted variables bias.

We also use cross-sectional variation to separate our competing hypotheses, and isolate economic mechanisms through which bank cross-monitoring benefits bondholders. We find that the effect on bond yields is larger for non-investment grade firms (a common measure of information opacity), contrary to the prediction of Sharpe (1990) and Rajan (1992). Furthermore, the benefit of a relationship is higher for firms with collateralized bank debt (Park (2000)), no CDS (Parlour and Winton (2013)), and dispersed bond ownership (Smith

and Warner (1979)). Overall, our cross-sectional results suggest that when the marginal value of bank monitoring is higher, bond yields are lower, consistent with the free-riding hypothesis.

Our tests focus on a sample of firms with both bank debt and public bonds, in order to separate the effect of bank monitoring from screening, since all of our firms have been successfully screened. In addition, we measure bond yields using secondary market spreads, rather than at-issue spreads. This is an important difference. Changes in secondary market yield spreads capture the real capital gain to current bondholders whereas changes in at-issue spreads capture changes in shareholder wealth. Our focus on secondary market spreads allows a direct measurement of the effect of bank cross-monitoring on bondholder wealth. Secondary market spreads are also more likely to reflect that current credit worthiness of the firm while at-issue spreads may include financial market frictions such as coordination costs among underwriters, stock liquidity, or banking networks. The difference here is similar to using a tender price to measure the gains to shareholder wealth from a merger announcement, as opposed to the change in market price. In both cases, the market price is more likely to reflect the true synergies from the deal. To our knowledge, this paper is the first to uncover the effect of a banking relationship on secondary market yields.

Our definition of a banking relationship is deliberately broad. We simply measure whether a firm's current loan is from a lender it has borrowed from before. By contrast, Datta et al. (1999) and prior studies, discriminate between firms with bank loans, and firms without bank loans. We believe our distinction is important; Rauh and Sufi (2010), and Colla et al. (2013) show that the characteristics of firms that concurrently use multiple debt sources are different from those that borrow from one source, inducing a selection bias. By requiring all firms in our sample to have bank and public debt, our tests are less vulnerable to selection bias, although our external validity is obviously mitigated.

Our results contribute to the literature on bank monitoring, a firm's cost of debt, and the determinants of corporate yield spreads. Some studies show that a banking relationship leads to lower loan spreads and better loan contract terms (Bharath et al. (2009), Karolyi (2018)). However, if a banking relationship also leads to higher public debt spreads, the net welfare effect might be negative for firms with concurrent bank and public debt. Our

results suggest that the net effect of bank monitoring is positive.

Our work is related to other studies that document benefits from cross-monitoring. For example, Booth (1992) finds that cross-monitoring by bond rating agencies is associated with smaller loan spreads. More directly, Datta, Iskander-Datta, and Patel (1999) find that firms with bank debt pay lower spreads the first time they issue public bonds. While our results are consistent with these studies, they are also distinct in a number of ways. First, past studies may confound the effects of bank monitoring with the screening that results from loan approval, introducing a potential selection bias. Since we isolate bank relationships conditional on a loan existing, our approach is more focused on ex post monitoring. Second, we sharpen our hypothesis tests using instrumental variables and a quasi-natural experiment with an aim towards making stronger causal inferences than in previous studies. Third, our use of market bond spreads rather than at-issue bond spreads is an important innovation because it removes the potentially confounding effects of changes in equity valuation around bond issue dates. Fourth, relative to previous studies, we use a broad sample over a long period (23 years). Lastly, it is not clear whether the results from early studies can be extrapolated forward because the incentives to monitor have changed significantly over the past 30 years as banks have moved from an originate-to-hold to an originate-to-distribute model. While our results do not overturn prior conclusions, they do make more robust causal inference about the magnitude, importance, and generality of a first-order theoretical prediction about the capital formation process.

The remainder of this paper is organized as follows: In Section 2, we present our sample construction procedure and descriptive statistics. In Section 3, we present our empirical methodology and primary results. We present robustness tests in Section 4, and conclude in Section 5.

II. Data Description

A. Sample Construction

To construct our sample, we use syndicated loan data from Loan Pricing Corporation's (LPC) DealScan database merged with bond price data from Mergent's Fixed Income Se-

curities Database (FISD), the National Association of Insurance Commissioners (NAIC), and the Trade Reporting and Compliance Engine (TRACE). We also use equity data from CRSP, financial data from Compustat Industrial Annual, analyst data from I/B/E/S, institutional ownership data from Thomson Financial 13F Database, CDS spread data from Markit, data on institutional investors' bond holdings from Lipper eMAXX, and firm year of incorporation data from a variety of sources (Field and Karpoff (2002), Fink et al. (2010)).

Data on bond issues come from Mergent FISD. We begin with a sample of 335,982 bonds issued between 1994 and 2016 (secondary market bond prices are only available starting in 1994). We focus our analysis on U.S. firms, deleting bonds issued by non-corporate issuers (150,202) or issuers with non-U.S. mailing addresses (68,380). To simplify calculations of yield to maturity, we delete bonds with non-fixed coupons (98,215), or bonds missing interest frequency information (959). Next, we eliminate bonds that are exchangeable, putable, convertible, payinkind, perpetual, or that have credit enhancements (22,063). These filters ensure that yield spreads are driven by the creditworthiness of the issuer and not confounded by guarantees. After applying the filters above, we are left with a sample of 23,496 bond issues from 2,790 corporate issuers. Of the remaining bonds, we match 99 percent (23,226 bond issues from 2640 issuers) to firm-level accounting information in Compustat.[6]

To track bond yields over time, we obtain secondary market prices from the National Association of Insurance Commissioners (NAIC) and TRACE.[7] NAIC data cover the first half of our sample, from January 1994 to June 2002, and TRACE data cover the rest – from July 2002 to June 2016.[8] Beginning in January of 1994, NAIC data cover all bond transactions by Life Insurance Companies, Heath Maintenance Organizations, and Property and Casualty Companies. This database is representative of corporate bond transactions because insurance companies hold about half of outstanding non-financial corporate bonds,

[6] For each bond in our sample, we obtain the associated issuer CUSIP from FISD. We then match this CUSIP to Compustat using the historical CUSIP (NCUSIP). We also include all other unmatched bonds that FISD assigns to the same issuer by using the issuer's primary identifier in the FISD database (*Agent ID*). For the remaining unmatched bonds, we use the link file provided by WRDS bond data, and S&P's Ratings Xpress link file, which contains 9 digit CUSIP's and associated Compustat identifier, gvkey. To minimize data errors, we manually verify each match to ensure that the company name is the same in Compustat and Mergent FISD *at issuance*.

[7] We use trace data summarized by WRDS bond returns, which is a combination of TRACE enhanced and TRACE.(see https://wrds-web.wharton.upenn.edu/wrds/support/Data/WRDS_Corporate_Bond_Database_Manual.pdf for more details)

[8] See Schestag et al. (2016) for a more detailed description of the TRACE data

according to data on bondholdings from Lipper eMAXX.

To reduce reporting errors, we average trading prices daily. Yield to maturity, modified duration, and bond convexity are computed each month using the last available average daily price. Next, yield spreads are calculated by subtracting from a bond's yield to maturity, the yield of a treasury security of similar duration. Government bond yield data comes from the Federal Reserve's H15 reports. Our final yield-spread data is a bond-month panel with monthly yield spread for each bond from the maximum of its offering date and January 1994 to the minimum of its maturity date and June 2016. We obtain secondary price data on 8,812 bond issues by 2,462 corporate issuers. Figure I shows the time series of yield spreads over the sample period. The levels and variation are consistent with prevailing yield spreads reported in prior studies.[9]

[INSERT FIGURE I ABOUT HERE.]

To construct measures of bank relationships, we turn to Loan Pricing Corporation's (LPC) DealScan database, which reports loan details from syndicated and bilateral loans collected from SEC filings and self-reporting lenders. Following prior literature, we exclude loans obtained by financial firms (SIC 6000 – 6999) and utilities (SIC 4900 – 4949). Also, we include only completed dollar-denominated loans between 1994 to 2016 that can be matched to the previously constructed FISD to Compustat linkfile.[10]

Next, we classify firms into two groups based on whether they have a banking relationship. Following Bharath et al. (2009), we define a firm-year banking relationship dummy, *Banking relationship*, which equals one if the borrower's lead lender on its current loan was also its lead lender on any other loans (*package* in DealScan) originated over the *prior* five years.[11] If a firm has two or more loans in a year and one of them is a relationship loan, the firm is classified as having a banking relationship.

In a syndicated loan, the lead bank has primary responsibility for ex ante due diligence

[9] See, e.g., Figure 3 in Campbell and Taksler (2003) and Figure 2 in Bongaerts et al. (2012).

[10] Our final sample comprises 1,429 U.S. firms with concurrent syndicated loans and bonds outstanding that have secondary market price data.

[11] Our results are not sensitive to the definition of the look-back period or banking relationship. Limiting the look-back period to three years or placing no constraint on the look-back period produces similar results, which can be provided upon request. Changing the definition a banking relationship to the fraction of all loans provided by the lead arranger over the *prior* five years also produces similar results as shown in Table 3.

and ex post monitoring of the borrower (Miller (2006)). Thus, we consider only lead banks in our relationship measure. Following Ivashina (2009), we identify the lead bank as the administrative agent. If a loan syndicate has no administrative agent then lenders acting as an agent, arranger, bookrunner, leadarranger, lead bank, or lead manager are identified as lead arrangers. To ensure relationships aren't confounded by bank mergers and acquisitions, we aggregate lenders to the parent company.

Each borrower in the firm-year dataset of new loans is matched to firm-month yield spread data using the Chava and Roberts (2008) linkfile and fuzzy name matching.[12] For each new loan obtained by the firm, we keep the closest yield spread information *following* the month the new loan was obtained but within the same year (yield spread information is available, in the month following loan origination, for 80% of sample observations). This procedure ensures that loan transactions are known to bondholders when a bond transaction takes place. Furthermore, including yield spreads one month to a year after loan origination prevents us from biasing our sample towards the most actively traded bonds, since most bonds seldom trade (Robertson and Spiegel (2017)). For firms with multiple bonds, we calculate value-weighted yield spread, duration, and convexity, using market prices and offering amounts to construct weights. Our final loan-spread dataset consists of 6,816 firm-year observations for 1,429 borrowing firms with syndicated loans and public debt outstanding from 1994 to 2016.

We complete our sample construction by including firm-level characteristics from Compustat, data on number of analysts reporting earnings per share (eps) from I/B/E/S, fraction of equity held by institutional investors from Thomson Financial 13F, idiosyncratic volatility to the CRSP value-weighted index and market capitalization from CRSP, CDS spread data from Markit, data on institutional investors' bond holdings from Lipper eMAXX, and firm year of incorporation data from various sources.

[12] We manually verify each match to minimize data errors.

B. *Summary Statistics*

Table I presents summary statistics. All variables are winsorized to minimize the influence of outliers.[13] The average yield spread over the sample period is 336 basis points (bps) and the median is 274 bps. On average, 73% of firms have a banking relationship. The fraction of firms with a banking relationship is relatively stable over the sample period. The average sample firm has about $2.77 billion in bank loans and $2.85 billion in senior unsecured public debt outstanding.[14] Since we have a 23 year panel, we adjust all dollar amounts for inflation using the Consumer Price Index.[15]

[INSERT TABLE I ABOUT HERE.]

The average time to maturity of outstanding bonds is twice that of bank loans at 4 years. About half of all new loans have financial maintenance covenants and about a third include a dividend restriction provision. The most prevalent bond indenture covenant, at 82% of the sample, is a restriction on mergers. About 70% of sample firms have a cross-acceleration provision in their indenture. Of the bonds outstanding during the sample period, 77% are callable and 3% are issued using medium-term note programs.

The average firm has an investment grade rating (rating of BBB-, which has a numeric value of 13), about 11 equity analysts reporting earnings per share, is about 65 years old (number of years since incorporation), and is located about 473 miles away from the closest lender on its loan syndicate.[16]

C. *Univariate comparisons.*

Table II presents summary statistics for sub-samples split by banking relationship status. Firms without banking relationships have higher yield spreads (about 86 bps higher, significant at a 1% level), consistent with the free-riding hypothesis, and borrow smaller amounts

[13] Results are similar without winsorizing or winsorizing at different levels.

[14] Since most loans in our sample are lines of credit, the amount of loans outstanding is an upper bound on the actual amount borrowed. Banks in this paper refers to all lenders in DealScan, since about 80 percent of lenders in our sample are U.S. commercial banks.

[15] CPI data, in 2009 dollars, are downloaded from the Federal Reserve Bank of St. Louis website. We use the Personal Consumption Expenditures Excluding Food and Energy series available at https://fred.stlouisfed.org/series/PCEPILFE. Our results are not qualitatively sensitive to this inflation adjustment.

[16] Higher numeric values of ratings denote higher credit quality. Rating are converted into numeric values from 1(C) to 21 (AAA).

from the syndicated loan and public debt markets. The characteristics of unsecured debt issued by firms with banking relationships are largely similar to those of firms without banking relationships: both groups issue bonds with similar maturities, indenture covenants, and trade frequency.

[INSERT TABLE II ABOUT HERE.]

Figure II presents average yields over time for both firms with and without a bank relationship. There is a clear pattern in the data. Firms with relationship loans consistently pay lower spreads than firms without relationship loans over the sample period. This pattern isn't specific to a particular period, and the magnitudes are, roughly speaking, consistent over time.

[INSERT FIGURE II ABOUT HERE.]

However, as the last ten rows of Table II show, characteristics of firms with a banking relationship differ from those of firms without a banking relationship. Thus, the univariate difference in yield spreads might just reflect underlying differences in firm characteristics.

III. Multivariate Regression Analysis

We first estimate the spillover effects of relationship loans on public debt spreads using multivariate regressions. Next, we augment our controls variables by including firm-fixed effects to eliminate cross-sectional heterogeneity. Furthermore, we test cross-sectional predictions of theory that are unique to each hypothesis, and conclude by verifying the robustness of our results using instrumental variables and a natural experiment.

A. Pooled OLS

We begin with the following pooled regression model:

$$\begin{aligned} \textit{Yield Spread}_{it} = \alpha_0 + \beta_1(\textit{Bank Relationship}_{it}) + \sum_{j=1}^{J} \gamma_j(\text{Firm Characteristics}_{itj}) \\ + \sum_{k=1}^{K} \nu_k(\text{Bond and Loan Characteristics}_{itk}) + \lambda_t + \epsilon_{it}. \end{aligned} \tag{1}$$

Variable subscripts, i denotes firms and t denotes time. λ_t is a dummy for each year, to control for systematic time effects like macroeconomic conditions. *Yield Spread* is the value weighted yield spread on all a firm's outstanding bonds following its most recent syndicated loan. Yield spreads are measured at least a month post loan initiation but within the same year. Measuring yield spreads post loan origination mitigates endogenous loan origination that could result from recently reduced spreads. We measure *Bank Relationship* as a dummy equal to one if the borrower has loans arranged by the same lead bank on its current loan over the *prior* five years.

Firm Characteristics are accounting variables that are correlated with bond yields and banking relationships as shown by prior research. All firm characteristics are matched to yield spread data with a 6-month (minimum) lag to ensure that they are known to bondholders prior to bond transactions.[17] We control for firm risk by including *Log Market Equity* (log of market equity), *Firm Age* (since incorporation), and *Number of Analysts*, (analysts reporting earnings per share). We expect firms that are larger, older, and have more analyst coverage to be less risky since they are better diversified and well known to bondholders. Thus, we expect these variables to have a negative effect on yield spreads.

To control for the riskiness of the firm's debt we include *Profitability* (net income to sales), *Interest Coverage* (net income to interest expense), *Leverage* (short and long term debt to assets), *Rating* (S&P's senior unsecured debt rating) and *Equity volatility* (standard deviation of the previous 250 previous daily returns prior to loan initiation).[18] Equity volatility distinguishes bonds with similar ratings and reflects recent information about credit risk not yet incorporated into bond ratings (Campbell and Taksler (2003)). We expect firms with volatile stock returns and high leverage to have higher yield spreads. On the other hand, we expect profitable firms, firms generating enough cash flow to cover interest payments, and firms with a high credit rating to have lower yield spreads. To account for possible non-linearities between ratings and yield spreads, we use ratings dummies, one for each rating category.

[17] We use data from the same fiscal year as the bond price observation if the gap between the accounting data and price observation is 6 months or more apart. Otherwise we use data from the prior fiscal year. Including contemporaneous firm characteristics does not meaningfully affect our results.

[18] Results are unchanged, if we use the mean value of bond specific ratings

We also include *Market to Book* (a firm's market to book ratio, measured as total assets less book value of equity plus market value of equity to total assets) to control for the effect of growth opportunities on yield spreads. The effect of this variable on yield spread is ambiguous. Since firms whose value mostly consists of growth options are most vulnerable to the suboptimal investment problem (Myers (1977)), bondholders might demand higher spreads on debt issued by high market-to-book firms. On the other hand, high market-to-book might represent a high liquidation value of tangible and intangible assets in place, reducing ex ante yield spreads.

Bond Characteristics include bond specific futures and indenture covenants. We include dummies for the following indenture covenants: *Cross Acceleration* (cross-acceleration provisions), *Additional Debt* (restrictions on issuing additional debt), *Sale-leaseback* (restrictions on sale leaseback transactions), *Earnings Ratio* (restriction on interest coverage), *Dividend Restriction* (restriction of dividend payouts), and *Change in control* (a put provision against specified events). These covenants should be associated with lower yield spreads as they make a given issue safer. However, since covenants are typically attached to riskier issues, their overall effect on yield spreads isn't clear.

We also control for bond specific features such as the fraction of a firm's bonds outstanding that is callable (*Callable*), issued using medium term note programs (*Medium Term Note*), and shelf registered (*Rule 415*). Callable bonds give an issuer the option to retire the bonds when it is most favorable to the issuer, such as when interest rates fall. As such this option should be associated with higher yield spreads. Since large and well known firms typically have medium term note programs and use shelf registration, we expect these variables to be negatively correlated with yield spreads. Furthermore, we control for bond market liquidity using the variables *Log Public Debt* (natural log of the total public debt outstanding) and *Log Trades* (natural log of the number of trades in all the firm's outstanding bonds in the month yield spread is measured). We expect higher values of these variables to be associated with bonds that are easier to trade. Hence, we expect these variables to be negatively correlated with yield spreads. Finally, we control for term structure effects on bond yields by including bond duration, current stock market return, and the prevailing

moody spread.[19]

We control for loan specific features, *Loan Characteristics*, using the variables *Secured* (a dummy equals one if a loan is secured by collateral), and *Number of Deals* (Total number of prior syndicated loans (packages) a firm has ever obtained). We include these variables to better delineate the effect of monitoring that comes from having a banking relationship from the effect of loan contract terms on yield spreads. Because loans that are *Secured* effectively subordinate senior unsecured public debt holders, we expect this variable to positively correlate with yield spreads. Table III shows a correlation plot between the main variables used in this study

[INSERT Table III ABOUT HERE.]

The results from regression equation (1) are presented in columns (1) and (2) of Table IV. To ease interpretation and comparison, we standardize all continuous variables to have zero mean and unit variance. Across all three specifications, we see that having a banking relationship is associated with an economically meaningful and statistically significant decrease in yield spreads. Having a banking relationship is associated with 86 bps lower yield spreads and conditionally associated with 16 bps lower yield spreads. This result is equivalent, in sample, to about a two notch increase in credit rating (to be precise, 1.9 notches including pluses and minuses), and a standard deviation increase in profitability, unconditionally. The relationship between our control variables and yield spreads is consistent with prior studies.

[INSERT TABLE IV ABOUT HERE.]

The point estimate from the regression of yield spreads on a measure of banking relationship is consistent with the free-riding hypothesis and inconsistent with the bank predation hypothesis or the syndication hypothesis, conditional on observed covariates. However, as we saw in Table II, if firms with relationship loans differ from firms with non-relationship loans on observed covariates, both groups are also likely to differ on unobserved covariates. Our estimate of the effect of a banking relationship might just reflect this unobserved difference.

[19] Moody spread is defined as the difference between the yield on seasoned corporate bonds with an Aaa rating and those on bonds with a Baa rating.

Interpreting the point estimate from regressing yield spread on banking relationship as the causal effect of a banking relationship on yield spread relies on the assumption that selection bias (the difference between the yield spreads on relationship firms' bonds if they had no relationship and non-relationship firms' bonds) is zero. This selection bias will be non-zero if an omitted variable is correlated both with yield spreads and having a banking relationship. The set of possible omitted variables that might lead to a non-zero selection bias can be split into confounders that are fixed, don't vary with time, and those that vary with time. We deal with the former set of confounding variables by augmenting equation (1) with firm-fixed effects.

B. Firm Fixed Effects

In this section, we report results from fixed effects specifications of the form:

$$\begin{aligned} \textit{Yield Spread}_{it} = \alpha_i + \beta_1(\textit{Bank Relationship}_{it}) + \sum_{j=1}^{J} \gamma_j(\text{Firm Characteristics}_{itj}) \\ + \sum_{k=1}^{K} \nu_k(\text{Bond and Loan Characteristics}_{itk}) + \lambda_t + \epsilon_{it}. \end{aligned} \tag{2}$$

where α_i is a dummy for each firm that absorbs all time-invariant firm-specific omitted variables that drive yield spreads. While firm fixed effects mitigate the influence of time-invariant unobservables, it may also attenuate our estimate of β_1 because firms with no variation in banking relationship status or firms that only appear once in the sample attenuate β_1 towards zero. The implicit banking relationship measure is zero for both groups because these firms have no within-firm variation in banking relationships.

Columns (3) to (6) of Table IV present our results. Column (3) includes only firm-fixed effects, column (4) includes firm and time fixed effects, column (5) replace our measure of banking relationship with the variable *Relationship 2*, which is the fraction of all loans over the prior five years obtained from the lead arranger on the current loan. For completeness, column (6) reports results from a first-difference specification.

Including firm-fixed effects does not meaningfully change our estimate of the effect of a banking relationship on yield spreads. For example, in columns (3) of Table IV, the point estimate of the effect of a banking relationship goes from a 17 pbs reduction in spreads, using

pooled OLS, to 16 bps reduction when we include year fixed effects, and a 15 bps reduction (columns (4)), when we include year and firm-fixed effects. This is not only statistically significant, but also economically meaningful; this effect is equivalent, in sample, to about a two notch credit rating upgrade. These results suggest that time-invariant unobserved variables are unlikely to be confounding our inferences on the effect of a banking relationship. Furthermore, as shown in column (5) the effect a relationship loan is not sensitive to our measure of banking relationship.

Fixed-effects estimation relies on the assumption of strict exogeneity for unbiasedness. In our setting, this implies that having a banking relationship in one period is uncorrelated with future shocks to yield spreads. As we will show later, however, this assumption is unlikely to be satisfied in our setting (for example, we show that, after the July 2014 oil shock, prices on bonds of oil firms with an existing banking relationship dropped less than prices on bonds of oil firms without a relationship). To test whether our estimates are sensitive to the strict exogeneity assumption, in column (6), we estimate equation (2) in first-differences, which relies on the weaker assumption of contemporaneous exogeneity. Results from using first-differences are similar to those from fixed-effects regression, albeit less precisely estimated, owing to a significantly smaller sample size.

C. Cross Sectional Sample Splits

In this section, we dig deeper into the cross section of firms to reveal the mechanism that connects bank relationships to bond yields. These sample splits are designed to tease out specific predictions from our competing hypotheses. These tests also help identify the economic mechanism at work because any remaining confounding covariates must meet the additional criterion of consistency with cross-sectional results. Our estimation proceeds following the specification in equation (2) with cross-sectional interations.

Our first cross-sectional split is based on bondholder concentration. Under the free riding hypothesis, banking relationships should have a stronger effect on yield spreads if bond ownership is dispersed because the high coordination costs of dispersed ownership (Davydenko and Strebulaev (2007)). Alternatively, if the bank predation or syndication hypothesis holds, then the prediction is reversed because the bank is an additional creditor

bondholders have to negotiate with in distress and there are no offsetting gains, such as a reduction in bondholders' monitoring costs.

To test this hypothesis, we measure bondholder concentration with the Herfindahl-Hirschman index (HHI) of bondholdings. We proxy for renegotiation frictions using *Low Concentration*, which is a dummy equals one if the firm has a below median value of the HHI measure. Bondholdings are collected from eMAXX. Our results are presented in Table 4. Column (1) of Table 4 reports a stronger effect for firms whose debt is held by more dispersed bondholders. This evidence is consistent with the free-riding hypothesis as it suggests that banks lower the risk of strategic default by monitoring firms.

[INSERT TABLE V ABOUT HERE.]

The effect of a banking relationship may also depend on bondholders' incentives to monitor given the cost of hedging default risk. For example, firms with credit default swaps (CDS) may be easier for bondholders to hedge. Another reason a banking relationship might benefit such firms less is because bondholders might expect banks to weakly monitor such firms as banks can directly lay off credit risk by purchasing CDSs (see, e.g., Parlour and Plantin (2008), Parlour and Winton (2013)). If, on the other hand, banks are net sellers of CDS contracts for firms with whom they have relationships, the effect of a banking relationship could be stronger for firms with a traded CDS (Cecilia Cagilo (2016)).

To test this cross-sectional hypothesis, we construct *Has Traded CDS* which is a dummy variable equals one when a firm has a Markit CDS quote. From column (2) of Table V we see that firms with a traded CDS do not benefit from having a banking relationship. The regressions in Table V are estimated within-firm so the point estimate is identified from firms that transition from not having a traded CDS to having one, or vice-versa. Firms that transitioned from not having a traded CDS to having one have 26 bps higher yield spreads compared to firms with a banking relationship that never had a traded CDS during our sample period. All our results in this section are similar, or even stronger, in simple OLS splits without firm fixed effects. These results are consistent with the conclusion in Ashcraft and Santos (2009) and support the free-riding hypothesis by showing that bondholders value bank monitoring, at least as long as they believe the bank has sufficient incentives to monitor

the borrower.[20]

Seniority should also improve a lender's incentives to monitor (Park (2000)) since a senior lender has a higher marginal benefit from monitoring efforts. Since collateral grants a higher position on the seniority ladder, we test whether the cross-sectional effect of a banking relationship varies depending on whether collateral is pledged.

We measure *Secured* as a dummy variable equals one if a new loan is identified as secured with pledged collateral by DealScan. Under the free-riding hypothesis, firms with pledged collateral should benefit more from bank relationships because these firms are easier for banks to monitor. If the bank predation hypothesis dominates, firms with a secured loan should benefit less since pledged collateral gives that bank more bargaining power to extract value from the borrower by exercising more rigid oversight. If the syndication hypothesis dominates, then collateral values should have no impact on the cross-sectional effect of having a banking relationship.

The results in column (3) of Table V support the free-riding hypothesis. Firms with banking relationships who loans are secured have lower yield spreads than firms without banking relationships. These results support the prediction that bondholders expect the bank to monitor the firm since its incentives to monitor are high.

According to Myers (1977) Smith and Warner (1979), a dividend restriction can reduce suboptimal investment policy. Cash not used to pay dividends can be invested in positive NPV projects that would have been otherwise been forgone, mitigating the underinvestment problem (Myers (1977)). A loan covenant restricting dividends is more salient than a similar bond covenant because loan covenants are more restrictive (Verde (1999)). Thus, under the free-riding hypothesis, bondholders should benefit more from bank monitoring, if firms have dividend restrictions on their loans.

We capture the presence of a dividend restriction using the variable *Dividend Restriction*, a dummy equals one if a firm's loan covenants include a dividend restriction provision. From Column (4) of Table V we can see that firms that have a banking relationship with an attached dividend restriction benefit more from having a banking relationship. This

[20] Ashcraft and Santos (2009) find that the borrowing rates for firms that need monitoring increase after the introduction of CDSs.

results suggests that a dividend restriction is an important channel through which a banking relationship affects a firm's bond yields.

The work of Diamond (1991) suggests that the benefit of bank monitoring is lower for firms with a good capital market reputation since they risk losing that reputation if they act against investors interests. Thus we expect firms with a good reputation to benefit less from having a banking relationship. However, Rajan (1992) and Sharpe (1990) argue that opaque firms, without a good reputation, are especially vulnerable to bank predation. The syndication hypothesis predicts no causal effect of reputation on monitoring. We follow Sufi (2007) and proxy for borrower reputation using the variable *Junk*, which is a dummy equals one if a firm's issuer rating is non-investment grade. As we can see from column (5) of Table V, the benefits of a banking relationship are much higher for non-investment grade firms. This result suggests that bondholders value bank monitoring especially for firms without an established reputation.

D. Instrumental Variables Estimation

In sections III.A to III.C we present strong evidence that bank relationships lower yield spreads, *ceteris paribus*. However, it may be that estimation of a causal relationship is confounded by other omitted variables that vary over time or might be correlated with our cross-sectional splits. Further, there may be some reverse causality if banks choose to initiate relationships with firms that are expected to have lower yield spreads. To mitigate these identification concerns, we reestimate our basic regression framework in section III.A using two plausibly exogenous instruments for a bank relationship.

Our first instrument is the geographical distance between a firm and its lender. A firm with headquarters close to its bank is more likely to have a relationship because the bank can easily gather information on the firm, facilitating relationship development (Bharath et al. (2009)). For example, a close bank may have more intangible information about the firm, and the competence and character of its management. For each new loan, we measure the distance to the firm for each member of the loan syndicate and keep the minimum distance. We then split the sample in distance quintiles and create a dummy variable (*High Distance*) for firms in the highest distance quintile. As Figure III shows, almost every state in the

U.S. is represented in our sample. While there is some expected geographical concentration (e.g., New York) there is also considerable geographic dispersion.

[INSERT Figure III ABOUT HERE.]

Our second instrument is the median size of bank branch deposits in the county in which a firm is headquartered. Firms headquartered in counties in which banks have a low supply capital are more likely to have a relationship because such banks are more likely to lend to the firm. To construct our second instrument for each firm we calculate the median amount of bank branch deposits for banks in the firm's county. Next we split the sample into bank branch deposit quintiles and create a dummy variable (*Low Bank Deposits*) for firms in the lowest quintile. Both instruments coded such that firms in the ones group are less likely to have a banking relationship. Both instruments generate plausibly exogenous variation in bank relationships because neither is likely to be a choice variable that bondholders use to set yield spreads. Moreover, both variables are predetermined geographic constraints that are not chosen by the firm, at least not in any practical contemporaneous sense.

Table VI describes our IV results. Both instruments are relevant. Columns (1) and (2) of Table VI show that both the distance and bank deposits dummies are significant determinants of a bank relationship. Conditional on second stage covariates, being in the top quintile of distance from lender (*High Distance*) is associated with a 10 percent decrease in the probability of obtaining a relationship loan. Similarly, being in the bottom quintile of local availability of bank branch deposits (*Low Bank Deposits*) decreases the probability of obtaining a relationship loan by 3 percent.

[INSERT TABLE VI ABOUT HERE.]

The last four rows of Table VI present several IV post estimation statistics. First, the *Kleibergen-Paap rk LM*, which tests the null hypothesis that our instruments are not "relevant" is soundly rejected. Next, we assess the strength of the correlation between our instruments and banking relationships using the *Cragg-Donald Wald F* statistic, which is a weak instruments test (Stock and Yogo (2002)). A *10% Stock-Yogo critical value* of 19.93 implies that our instruments are not weak under very reasonable assumptions of bias relative to OLS. The last row of Table 5 presents the *Hansen J P-val* which indicates ($p = 0.31 >$

0.05) that the overidentifying instruments are valid. Overall, our IV estimation appears to be well specified.

Column (3) of Table VI reports the results of our second stage IV estimation. The effect of instrumented banking relationship on yield spreads is consistent with our previous results. However, the magnitude of the effect is quite large at about thirteen times the magnitude of our pooled and fixed effects estimates. One explanation for this is the "local" nature of the IV estimate. "Compliers" are the subset of firms for whom distance and the number of surrounding banks significantly increase the probability of having a bank relationship. Since distance to closest lender is a stronger instrument, as reflected by its higher first-stage t-statistic, the observations with the smallest residuals in the first stage are those for whom distance is highly correlated with bank relationship. As explained in Sufi (2007), information asymmetry is likely to be severe for these firms. Since bondholders are more likely to monitor firms with high information asymmetries, the spillover effects of relationship loans might be greatest for these firms, hence the large point estimate. Because firms with high information asymmetry may not represent all firms with public debt, we view the IV results as having less external validity than the fixed-effects or pooled-OLS results. Nevertheless, our IV estimates serve as a useful robustness test that, at a minimum, our results do not appear to be the spurious result of omitted variables or selection bias.

E. Evidence from a natural experiment

If bank monitoring is valuable to bondholders, it should be especially so when the marginal benefit of monitoring is high, for example during financial distress. Conversely, financial distress is also likely to be a time when the benefits of bank predation are particularly high. Distress, and the possible flattening of priority status during bankruptcy gives banks a strong incentive to renegotiate loan term to the potential detriment of bondholders. To test whether the cross-monitoring or bank predation hypotheses prevail during financial distress, we focus on a negative shock to asset values for a sub-sample of firms that experience a large unexpected decline in firm value. From a bondholder's perspective, a significant decline in firm value moves the firm closer to default, and raises both the marginal value of monitoring and the possibility of hold-up costs.

We focus on the sustained and severe drop in oil prices in 2014 (see Figure IV for a drop in the price of U.S. crude oil). This unexpected commodity price decline provides an nice opportunity to test whether some bondholders value the monitoring a bank relationship provides. If banks help mitigate moral hazard costs, then under the free-riding hypothesis, we expect a larger negative effect on yield spreads for firms without a bank relationship. Since this commodity price shock should only affect firms with exposure to oil prices, our quasi-experimental setting provides an opportunity for a triple-difference test of bank relationships by comparing firms with a bank relationship from before to after the shock between firms in the energy industry to non-energy control firms

[INSERT FIGURE IV ABOUT HERE.]

Figure IVb shows that, as expected, oil firm bonds prices fell with the drop in oil prices, increasing their yields. Figure Figure IVc also shows that the yield spreads of firms without a bank relationship increase much more. Overall, these results are consistent with the prediction that bank monitoring is valuable to bond investors in mitigating the cost of moral hazard. If the bank predation effect dominates, we would expect bond prices to fall since the likelihood of bondholder wealth expropriation by banks goes up driving up bond yields for firms with a bank relationship. We find no evidence of this in the data.

To quantify the magnitude of the difference in yields around the oil price shock in more detail we use a multivariate regression of the form:

$$\begin{aligned} \textit{Yield Spread}_{it} = \alpha_i &+ \beta_1(\textit{Bank Relationship}_{it}) * (\textit{Oil Firm}_{it}) * (\textit{Post Shock}_t) \\ &+ \beta_2(\textit{Bank Relationship}_{it}) + \beta_3(\textit{Oil Firm}_{it}) + \beta_4(\textit{Post Shock}_{it}) \\ &+ \beta_5(\textit{Oil Firm}_{it}) * (\textit{Post Shock}_{it}) \\ &+ \sum_{j=1}^{J} \gamma_j(\text{Firm Characteristics}_{itj}) \\ &+ \sum_{k=1}^{K} \nu_k(\text{Bond and Loan Characteristics}_{itk}) + \lambda_t + \epsilon_{it}. \end{aligned} \tag{3}$$

Where *Oil Firm* is a dummy variable equal to one if the firm has a primary SIC code included in 1200 – 2999, and *Post Shock* is a dummy variable equal to one if the observation

is after July 2014. The regressions are estimated at a bond-month level using one year of data before and after oil shock, a total of 24 months of data. The coefficient of interest, β_1, measures the difference treatment effect of a bank relationship on yield spreads for oil firms after the shock.

Table VII presents the results of our analysis. In row (4) of Table VII, we see that spreads for oil firms with a banking relationship increased by 253 basis point (bps) less than the spreads on bonds held by oil firms with no banking relationship. The magnitude of the effect here is similar to our IV estimation. Again, there is no evidence of predation during financial distress and the data appear to be more consistent with the cross-monitoring hypothesis. [21]

[INSERT TABLE VII ABOUT HERE.]

IV. Robustness Checks

We check the robustness of our estimates by changing by dependent variable to credit default swap (CDS) spreads, and by splitting the sample based on our two sources of bond price data. Changing the dependent variable is a further test of the internal validity of our results. Specifically, we want to rule out possible omitted variables that might have escaped the screens above but that might be unrelated to CDS spreads. Splitting the sample based on data source is a check of the external validity of our results.

Briefly, a credit default swap (CDS) on a firm protects its buyer by providing the buyer a lump-sum payment made by the seller in case of default. Like yield spreads, CDS spreads price firm default risk. Unlike yield spreads, which also also price interest rate risk, CDS spreads only price the credit risk of the firm. Thus, we expect banking relationships to have a similar effect on CDS spreads as on yield spreads. The yearly correlation between CDS and yield spreads ranges yearly from a high of 0.99 in 2002 to a low of 0.60 in 2010 (mean correlation over the sample period is 0.8). Since CDS and yield spreads are different measures of credit risk, some confounding variables that might simultaneously be correlated

[21] We also replicate the analysis in Table VII using a matched sample approach. We match bonds issued by oil firms after the shock with a bank relationship to control firms with similar firm and bond characteristics and find qualitatively similar results. Results are reported in the online appendix.

with a banking relationship and yield spreads might not be correlated with CDS spreads. For example, Bongaerts et al. (2011) show that the pricing of liquidity risk is different for derivatives, such as CDSs, than for positive-net-supply assets, such as corporate bonds. We use CDS quotes on U.S. dollar-denominated contracts with a five-year maturity from Markit, which covers most CDS contracts written on U.S.-based entities.

Table VIII presents the results from using CDS spreads as a dependent variable. Columns (1) and (2) show results using pooled OLS, and columns (3) and (4) show results using firm-fixed effects. Across all specifications, having a banking relationship is associated with reduced credit spreads. However, the inclusion of year-fixed effects in column (3) significantly reduces the point estimate of relationship loans and renders it insignificant. There are several reasons why this is the case. Parlour and Winton (2013) show that when banks can buy CDS protection, they might have reduced incentives to monitor the firm. Hence for firms with traded CDSs, we would expect bank cross-monitoring to have a reduced effect on yield spreads. Also, the effect of banking relationships on CDS spreads is less precisely estimated because we have fewer observations; fewer firms have traded CDS contracts than have outstanding bonds. Column (4) shows that non-investment grade firms with a banking relationship have lower CDS spreads that non-investment grade firms without relationships. This effect is consistent with our cross-sectional tests.

[INSERT TABLE VIII ABOUT HERE.]

While TRACE data on bond prices covers all bonds traded over the counter, 95 percent of all bonds, NAICS data only covers bond transactions by insurance companies. However, because insurance companies hold most bonds to maturity, observed prices of bonds sold might be non-random. If bonds in our NAICS sample trade as a result of distress events, such as a credit rating downgrade, our results might only be apply to distressed firms. To ensure that NAICS data is not driving our results, we split the sample based on the source of secondary market price data. Table IX presents the results and shows that our results are not driven by the source of bond prices.

[INSERT TABLE IX ABOUT HERE.]

V. Conclusion

We test three hypotheses about the impact of a banking relationship on bond yields. Fama (1985) argues that a bank loan renewal may dissuade other creditors from investing in duplicative monitoring. Similarly, Myers (1977) argues that a continuous lender relationship can solve the underinvestment problem, conditional on the costs of maintaining such a relationship. This allows bondholders to free-ride off of bank monitoring. At the same time, the "bank-predation" hypothesis stipulates that banking relationships increase a firm's cost of public debt as banks use the relationship to extract concessions at the expense of bondholders. Finally, the "syndication" hypothesis postulates that bondholders will not expect any positive spillovers from bank cross-monitoring because banks' reduced share of loans at origination and over the life of a loan gives them less incentives to conduct due diligence.

Our results are consistent the free-riding hypothesis. A banking relationship is associated with a 15 bps decrease in yield spreads. This magnitude is economically meaningful: equivalent to a two-notch credit rating upgrade or a 0.8 standard deviation increase in profitability. Consistent with beneficial cross-monitoring, the effects are stronger for firms where the marginal benefit of monitoring is expected to be higher (dispersed bond ownership, more collateral, junk debt, no traded CDSs, restricted dividend). Our results are robust to a battery of empirical tests, sample constructions, and experimental designs. Financial intermediaries have real effects on firm outcomes. A banking relationship is associated with a statistically significant and economically meaningful reduction in a firm's cost of public debt.

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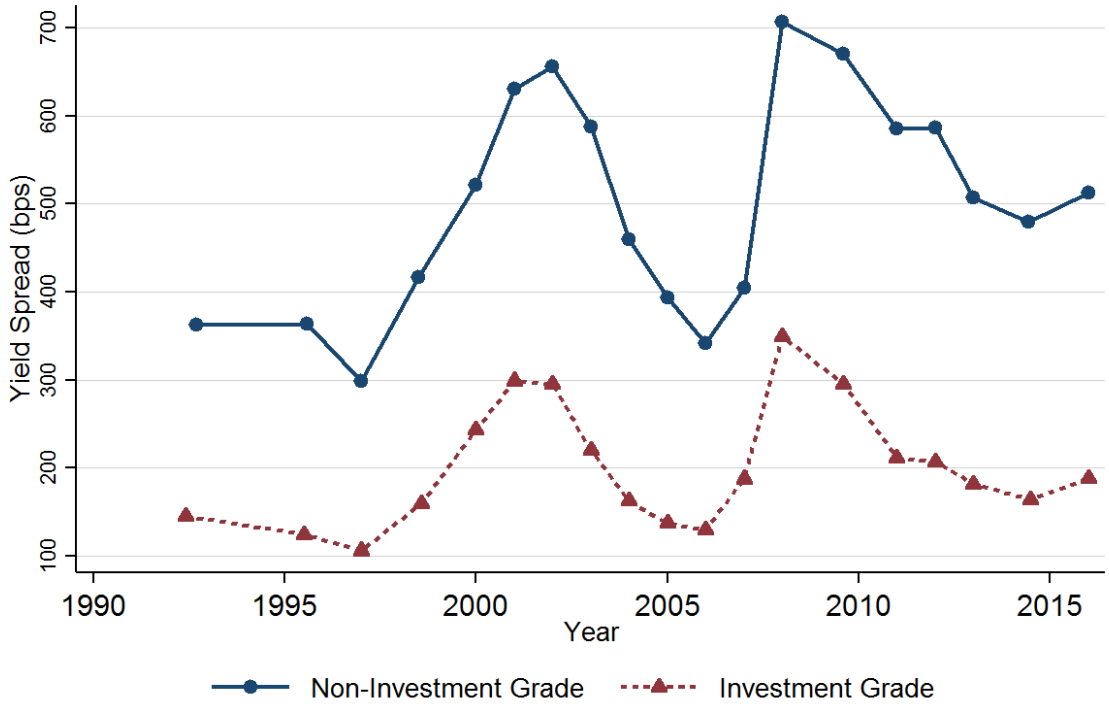


Figure I: Average yield spreads by rating category. This figure plots average yield spreads by rating category over the sample period. *Yield Spread* is the difference between the yield on a corporate bond and a treasury security of similar duration. *Investment Grade* is a rating from AAA to BBB− (22 to 13 on a numerical scale). *Non-Investment Grade* is a rating from BB to CCC− (12 to 1 on a numerical scale).

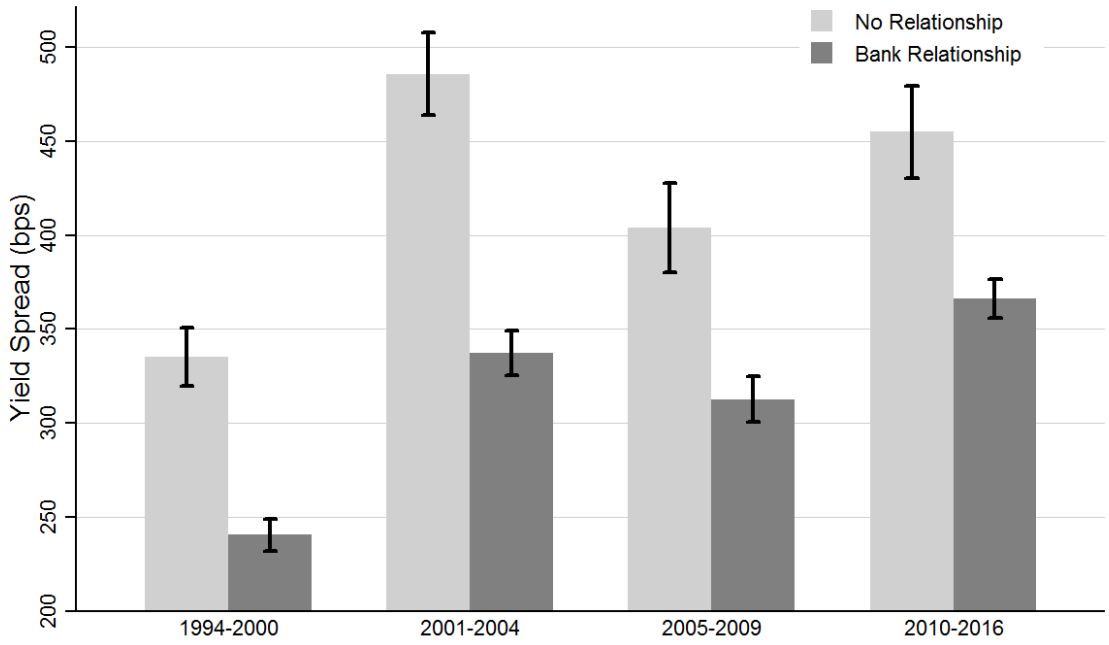


Figure II: Average yield spreads by banking relationship status. This picture plots the average yield spreads by banking relationship status over the sample period. The line above each bar represents 95% confidence intervals. For all new loans in a given year, *Banking relationship* is a dummy equal to one if over the past five years the borrower has loans arranged by the same lead bank.

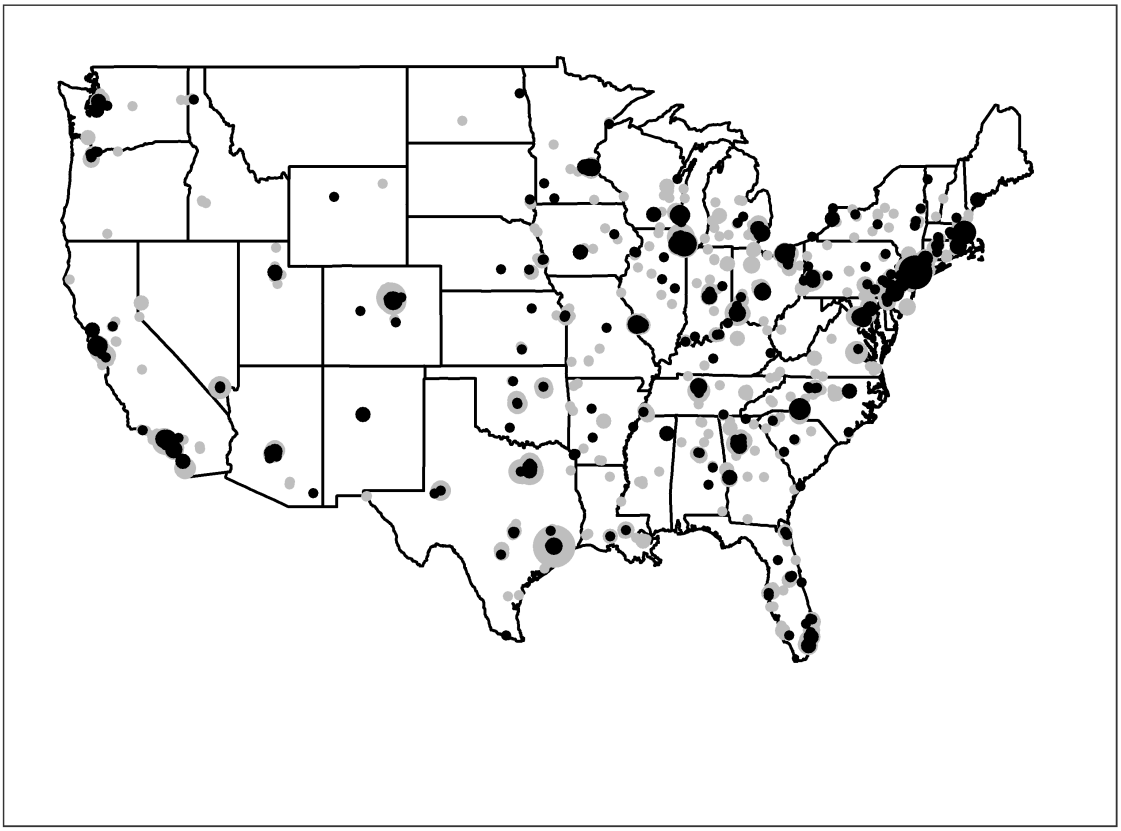
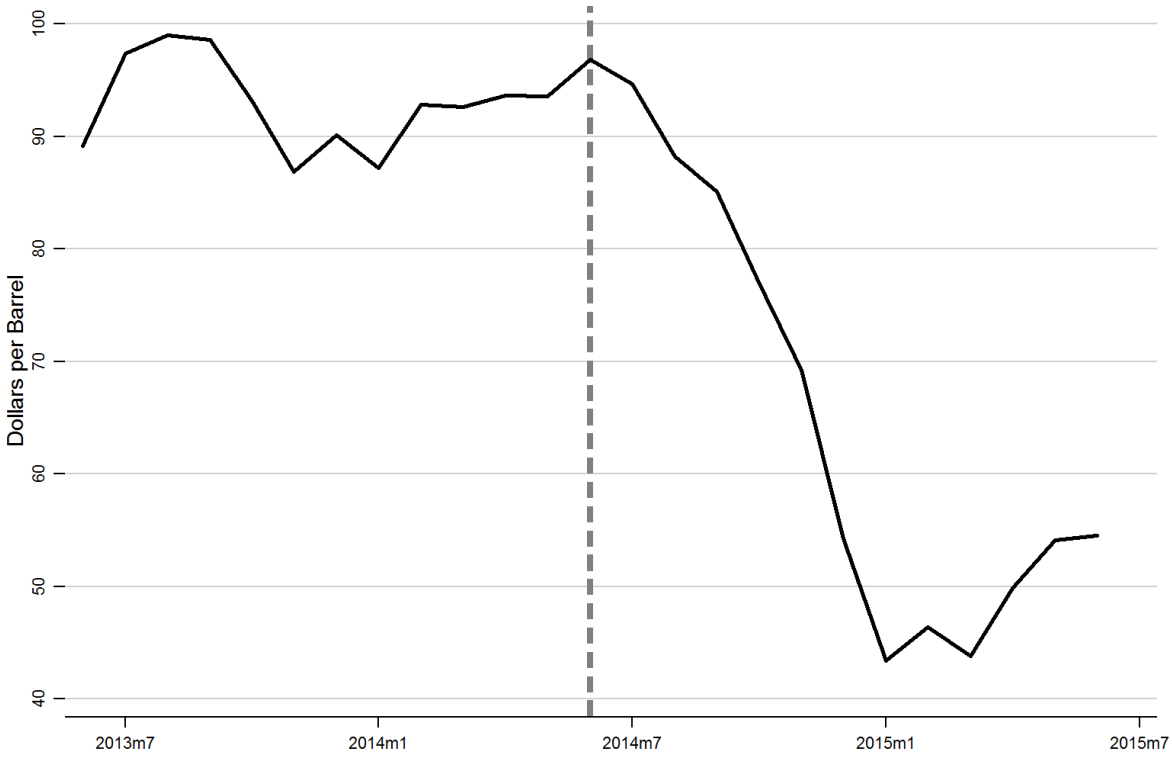
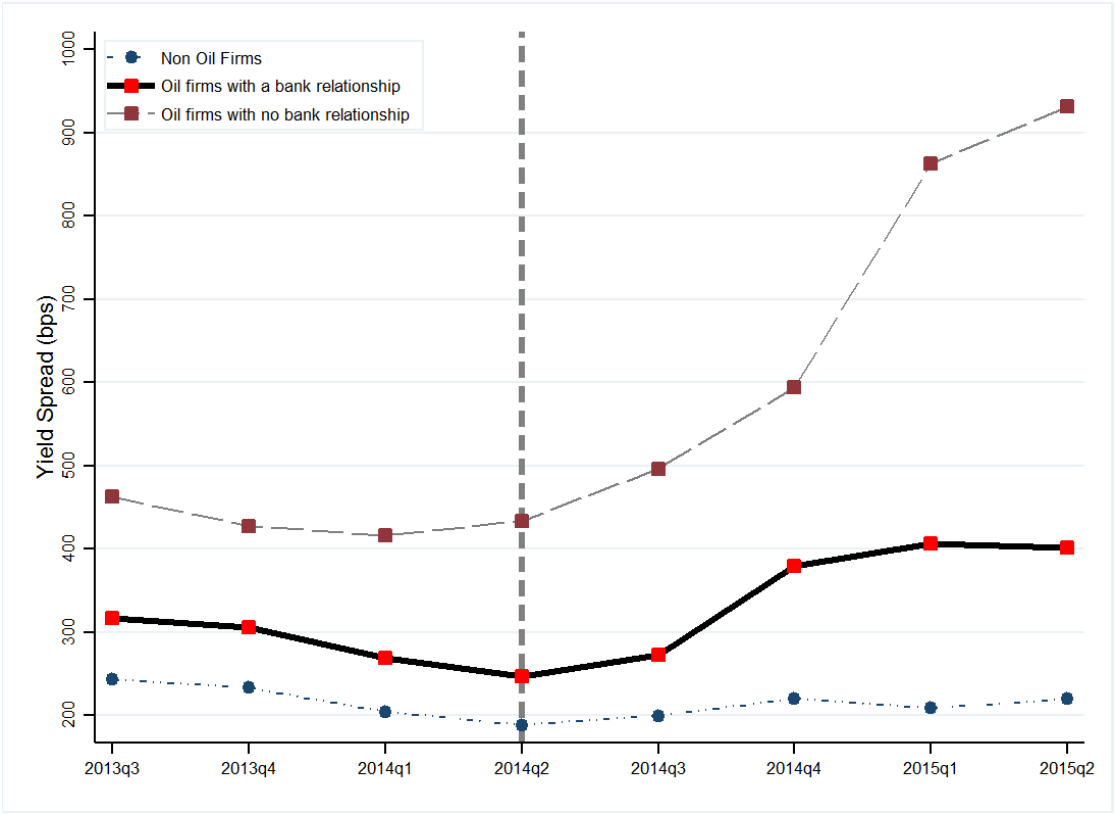


Figure III: Location of sample firms and Banks
This map shows the headquarters of firms and lead banks from whom the firms obtained syndicated loans. Gray dots show the location of borrowers and black dots show the location of the lenders. The size of each point is directly proportional to the number of sample firms (lenders) at that location. About 40 firms in our sample are headquartered in Houston Texas.



(a) Price of U.S. Crude Oil (West Texas Intermediate Crude).



(b) Effect of Oil Shock by banking relationship status

Figure IV: Impact of Oil Shock by Relationship Status.
This figure shows the impact of the exogenous supply shock to oil prices that began in July 2014. The gray dotted line shows the month of the shock, July 2014. Figure 1a shows the price of U.S. crude oil twelve months before and after the oil shock. Figure 1b shows the effect of the shock on bond yields of firms by whether they are in the energy industry (last line is for non-energy firms), and whether they have a bank relationship, conditional on being in the energy industry (top two lines). *Oil firms* (SIC 1200 – 2999) are identified using the Fama-French industry 12 classification. For all new loans in a given year, *Banking relationship* is a dummy equal to one if over the past five years the borrower has loans arranged by the same lead bank.

Table I: Summary Statistics.

This table presents yearly statistics of U.S. firms, excluding financial firms (SIC 6000 – 6999) and regulated utilities (SIC 4900 – 4949), with concurrent public debt and syndicated loans outstanding between 1994 and 2016. *Yield Spread* is the value-weighted difference between the yield on a firm's outstanding bonds and a treasury security of similar duration. *Bank Relationship* is a dummy equal to one if over the prior five years the borrower has loans arranged by the lead bank on any of its current loans. *Relationship 2* is the fraction of all loans over the prior five years obtained from the lead arranger on the current loan. *Bank Loans Outstanding* (*Public debt Outstanding*) is the amount of bank loans (senior unsecured public bonds) outstanding per year in billions of dollars ($B). *Market Equity* is the market equity of the firm calculated as end of year price times common shares outstanding. *Time to Maturity Loan (Time to Maturity Bond)* is the value-weighted time to maturity of new bank loans (senior unsecured bonds outstanding). *Has Loan Covenants* is a dummy equal to one if the firm has loan covenants reported by DealScan. *Secured Loan* is a dummy equals one if any loans that are part of a loan package are identified as secured. *Number of Prior Loans* is the total number of prior syndicated loan deals obtained by a firm. *Callable (Medium Term Note)* is the fraction of the firm's bonds outstanding that are callable (medium term notes). *Cross Acceleration Sale-leaseback, Change in control, Earnings Ratio, Additional Debt, or Merger restriction,* are dummies equal to one if a firm has the given covenant in it's bond indenture. *Duration* is bond duration measured in years. *Log Trades* is the log number of yearly trades in a firm's bonds. *Market Leverage* is a ratio of the book value of debt to the book value of debt plus the market value of equity. *Market to Book* is the ratio of total assets less the book value of equity plus the market value of equity to total assets. *Profitability* is the ratio of operating income net of depreciation to sales. *Firm Age* is number of years since *incorporation*. *Number Analysts* is the number of analysts reporting earnings per share. *Issuer Rating* is the issuer's S&P long term unsecured rating coded as 7 for AAA, 6 for AA, and so on. *Log Equity Volatility* is log of firm annualized common stock volatility (in %), calculated from previous 250 daily returns before loan initiation. Distance is the distance from the firm to its closest loan syndicate member in miles. All values are winsorized to mitigate the influence of outliers.

	Mean	Std. Dev	Min	25%	50%	75%	Max	N
Yield Spread (bps)	336.51	242.22	55.13	138.13	274.24	477.40	924.35	6,816
Bank Relationship	0.73	0.44	0.00	0.00	1.00	1.00	1.00	6,816
Relationship 2	0.63	0.40	0.00	0.25	0.75	1.00	1.00	6,288
Bank Loans Outstanding ($B)	2.77	2.90	0.22	0.75	1.67	3.59	11.08	6,816
Public debt Outstanding ($B)	2.85	3.38	0.22	0.60	1.37	3.70	12.69	6,816
Market Equity ($B)	9.66	14.85	0.15	0.88	3.13	10.67	56.95	6,816
Time to Maturity Loan (Years)	4.03	2.16	1.00	3.00	4.00	5.00	10.00	6,816
Time to Maturity Bond (Years)	8.43	6.09	2.00	5.00	7.00	10.00	26.00	6,816
Has Loan Covenants	0.52	0.50	0.00	0.00	1.00	1.00	1.00	6,816
Secured Loan	0.35	0.48	0.00	0.00	0.00	1.00	1.00	6,816
Number of Prior Loans	8.72	5.99	1.00	4.00	7.00	12.00	28.00	6,816
Callable	0.77	0.42	0.00	1.00	1.00	1.00	1.00	6,816
Medium Term Note	0.03	0.16	0.00	0.00	0.00	0.00	1.00	6,816
Cross Acceleration	0.63	0.48	0.00	0.00	1.00	1.00	1.00	6,816
Sale-leaseback	0.54	0.50	0.00	0.00	1.00	1.00	1.00	6,816
Change in control	0.46	0.50	0.00	0.00	0.00	1.00	1.00	6,816
Earnings Ratio	0.10	0.30	0.00	0.00	0.00	0.00	1.00	6,816
Additional Debt	0.35	0.48	0.00	0.00	0.00	1.00	1.00	6,816
Merger restriction	0.82	0.38	0.00	1.00	1.00	1.00	1.00	6,816
Duration	5.38	2.53	1.51	3.70	5.14	6.48	11.42	6,816
Log Trades	8.79	2.18	4.61	7.31	8.87	10.42	12.43	6,816
Market Leverage	0.33	0.21	0.05	0.16	0.29	0.47	0.78	6,797
Market to Book	1.30	0.65	0.55	0.82	1.10	1.59	2.97	6,220
Profitability	0.18	0.12	0.03	0.09	0.15	0.23	0.50	6,792
Firm Age (Years)	64.69	43.21	8.00	26.00	58.50	99.00	149.00	6,286
Number Analysts	11.51	7.74	1.00	5.00	10.00	17.00	27.00	6,816
Issuer Rating	13.18	3.54	7.00	10.00	13.00	16.00	22.00	6,094
Log Equity Volatility	3.60	0.41	2.92	3.28	3.57	3.88	4.40	6,353
Distance (miles)	473.42	475.42	1.58	76.35	298.73	759.37	1644.86	6,359

Table II: Descriptive Statistics by Banking Relationship Status.

This table presents yearly statistics of U.S. firms, excluding financial firms (SIC 6000 – 6999) and regulated utilities (SIC 4900 – 4949), with concurrent public debt and syndicated loans outstanding between 1994 and 2016, by banking relationship status . *Bank Relationship* is a dummy equal to one if over the prior five years the borrower has loans arranged by the lead bank on any of its current loans. Other variables are defined in Table I. All values are winsorized to mitigate the influence of outliers.

	No Banking Relationship		Banking Relationship		Test	
	Mean	Std. Dev	Mean	Std. Dev	Difference	t-stat
Yield Spread	398.77	323.65	313.61	268.85	85.17***	9.43
Bank Loans Oust.	1.98	2.76	3.40	4.12	−1.42***	−15.47
Public debt Oust.	2.54	4.53	3.63	5.55	−1.08***	−7.73
Market Equity	9.13	23.19	14.11	28.52	−4.98***	−6.95
Loan Maturity (Years)	4.27	2.30	3.88	1.93	0.39***	6.07
Bond Maturity (Years)	8.29	6.27	8.65	6.81	−0.36	−1.95
Has Loan Covenants	0.50	0.50	0.52	0.50	−0.02	−1.64
Loan is Secured	0.40	0.49	0.30	0.46	0.10***	7.05
Number of Prior Loans	6.17	5.03	9.67	5.81	−3.51***	−23.01
Callable	0.77	0.42	0.76	0.43	0.01	0.89
Medium Term Note	0.03	0.17	0.03	0.16	0.00	0.62
Cross Acceleration	0.65	0.48	0.62	0.48	0.02	1.62
Sale-leaseback	0.49	0.50	0.57	0.49	−0.08***	−5.55
Change in control	0.47	0.50	0.44	0.50	0.03	1.75
Earnings Ratio	0.07	0.25	0.11	0.31	−0.04***	−5.46
Additional Debt	0.38	0.49	0.32	0.47	0.06***	4.48
Has Dividend Restriction	0.43	0.49	0.39	0.49	0.04**	2.95
Merger restriction	0.79	0.41	0.84	0.36	−0.06***	−4.80
Duration	5.23	2.55	5.55	2.88	−0.32***	−4.16
Log Trades	8.70	2.39	8.75	2.28	−0.05	−0.77
Market Leverage	0.35	0.24	0.32	0.21	0.04***	5.31
Interest Coverage	9.60	15.08	10.66	13.86	−1.06*	−2.44
Market to Book	1.30	0.81	1.35	0.80	−0.05*	−2.17
Profitability	0.17	0.15	0.19	0.15	−0.01**	−3.04
Firm Age (Years)	58.96	42.90	69.77	45.57	−10.81***	−8.19
Number Analysts	10.05	8.26	12.71	8.24	−2.66***	−11.09
Issuer Rating	12.81	3.56	13.53	3.45	−0.71***	−6.47
Log Equity Volatility	3.73	0.46	3.56	0.42	0.17***	12.48
Distance	545.18	596.85	465.39	520.27	79.78***	4.47

Table III: Correlation between Variables

This table presents univariate correlations amongst several firm characteristics. All variables are defined in Table I. All values are winsorized to mitigate the influence of outliers.

Variables	Yield Spread	Bank Rel.	M Equity	Assets	Firm Age	Rating	Vol	CF Vol	ROA	Leverage	MtoB	Z-score	Cash	Coverage	IO	# Analysts
Yield Spread	1.00															
Bank Rel.	-0.16	1.00														
M Equity	-0.61	0.19	1.00													
Assets	-0.47	0.19	0.88	1.00												
Firm Age	-0.29	0.11	0.37	0.41	1.00											
Rating	-0.65	0.10	0.74	0.61	0.42	1.00										
Vol	0.62	-0.17	-0.49	-0.39	-0.32	-0.46	1.00									
CF Vol	-0.24	0.11	0.62	0.68	0.22	0.37	-0.16	1.00								
ROA	-0.08	0.04	0.16	0.06	-0.09	0.07	-0.08	0.12	1.00							
Leverage	0.49	-0.07	-0.58	-0.22	-0.16	-0.59	0.40	-0.17	-0.12	1.00						
MtoB	-0.30	0.04	0.40	0.03	0.01	0.37	-0.16	0.06	0.24	-0.59	1.00					
Z-score	-0.33	0.04	0.29	0.13	0.22	0.46	-0.31	0.05	-0.34	-0.48	0.27	1.00				
Cash	0.01	-0.04	0.07	-0.03	-0.05	-0.05	0.00	0.05	-0.07	-0.23	0.21	0.12	1.00			
Coverage	-0.35	0.06	0.47	0.25	0.12	0.54	-0.29	0.26	0.20	-0.67	0.49	0.47	0.25	1.00		
Institutional Ownership	-0.10	0.12	0.24	0.24	0.13	0.04	-0.17	0.08	0.00	-0.19	-0.05	0.09	0.12	0.16	1.00	
# Analysts	-0.45	0.15	0.75	0.70	0.18	0.55	-0.31	0.53	0.18	-0.40	0.28	0.18	0.04	0.38	0.22	1.00

Table IV: Effect of Banking Relationships on Yield Spreads.

This table presents OLS and fixed effects estimates of the following regression equation:

$$\textit{Yield Spread}_{it} = \alpha_i + \beta_1(\textit{Bank Relationship})_{it} + \sum_{j=1}^{J} \gamma_j(\text{Bond and Loan Characteristics})_{itj} + \sum_{k=1}^{K} \nu_k(\text{Firm Characteristics})_{itk} + \lambda_t.$$

All non-binary independent variables are standardized to have mean zero and unit variance to facilitate the interpretation of point estimates. Columns (1) to (3) present results from pooled ols regressions, and columns (4) and (5) present results from fixed-effects regressions. Column (6) is a first-difference regression. *Bank Relationship* is a dummy equal to one if over the prior five years the borrower has loans arranged by the lead bank on any of its current loans. *Relationship 2* is the fraction of all loans over the prior five years obtained from the lead arranger on the current loan. *Bond & Loan covenant controls* include: the number of bonds outstanding, the fraction of bonds outstanding that are medium-term notes, the fraction of bonds outstanding that are callable, dummies for whether a bond outstanding has a cross acceleration, sales-leaseback, change in control, earnings ratio, additional debt, dividend, or a merger restriction covenant, a dummy for whether a syndicated loan is secured, and the number of prior syndicated loan deals involving the firm. *Interest rate controls* include bond duration, stock market index return, and moody spread, defined as the difference between the yield on seasoned corporate bonds with an Aaa rating and those with a Baa rating. Other variables are defined in Table I. t-statistics, using robust standard errors clustered by firm, are in brackets. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	OLS		Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Relationship	-86.20***	-16.82***	-15.98***	-14.89***		-12.69*
	(-11.33)	(-3.52)	(-2.98)	(-2.90)		(-1.83)
Relationship 2					-17.21***	
					(-2.64)	
Log Market Equity		-24.71***	-13.42	-5.24	-9.62	30.83
		(-4.17)	(-1.36)	(-0.55)	(-0.98)	(1.53)
Market Leverage		13.91***	16.69**	18.50***	15.27**	18.47
		(3.15)	(2.27)	(2.59)	(2.03)	(1.55)
Profitability		-5.83**	-2.76	-3.31	-4.39	7.20
		(-2.37)	(-0.44)	(-0.56)	(-0.70)	(0.77)
Firm Equity Volatility		51.27***	60.54***	46.84***	46.88***	33.07***
		(14.91)	(15.62)	(9.93)	(9.53)	(4.29)
Log Public debt		-22.89***	-32.48***	-32.73***	-32.72***	-34.11***
		(-7.77)	(-8.00)	(-8.40)	(-8.02)	(-6.55)
Interest Coverage		-7.17*	-2.27	-3.08	-3.06	0.16
		(-1.86)	(-0.37)	(-0.52)	(-0.49)	(0.02)
Market to Book		-11.25***	-14.78***	-11.61**	-10.66**	-9.98
		(-4.11)	(-3.19)	(-2.45)	(-2.14)	(-0.94)
Firm Age		-3.90	76.46***	16.40	26.76	96.11
		(-1.41)	(3.61)	(0.71)	(1.12)	(0.86)
Number of Analysts		2.77	14.72***	9.18*	10.43*	4.35
		(0.80)	(2.82)	(1.68)	(1.84)	(0.36)
Duration		6.70***	9.09***	9.65***	9.84***	19.47***
		(3.41)	(4.19)	(4.57)	(4.61)	(7.26)
Observations	6816	5236	5236	5236	4885	2043
R^2	0.03	0.71	0.47	0.66	0.65	0.28
N. Issuers	1,429	1,139	1,139	1,139	1,078	637
Issuer FE	No	No	Yes	Yes	Yes	Yes
Year dummies	No	Yes	No	Yes	Yes	Yes
Ratings dummies	No	Yes	Yes	Yes	Yes	Yes
Bond & Loan covenant controls	No	Yes	Yes	Yes	Yes	Yes
Interest rate controls	No	Yes	Yes	Yes	Yes	Yes

Table V: Banking Relationships and the Cross-Section of firms

This table presents fixed effect estimates of the following equation:

$$\textit{Yield Spread}_{it} = \alpha_i + \beta_1 \textit{Bank Relationship}_{it} + \sum_{w=1}^{5} \pi_w (\textit{Bank Relationship}_{it} \times \text{Characteristic}_{itw}) + \sum_{j=1}^{J} \gamma_j (\text{Firm Characteristics})_{itj} + \sum_{k=1}^{K} \nu_k (\text{Bond and Loan Characteristics})_{itk} + \lambda_t.$$

Bank Relationship is a dummy equal to one if over the prior five years the borrower has loans arranged by the lead bank on any of its current loans. *Low Concentration* is a dummy equal to one if a firm's bondholder concentration, measured using the HHI of its bond holdings, is below the median concentration for all firms. *Has Traded CDS* is a dummy equal to one if a firm has a traded CDS. *Dividend Restriction* is a dummy equal to one if a firm has a loan covenant restricting dividend payout. *Secured* is a dummy equal to one if a firm's loan is secured by collateral. *Other Controls*, defined in Table I, include *Log Market Equity,Market Leverage*, *Profitability*, *Log Equity Volatility*, *Log Public debt Outstanding*, *Interest Coverage*, *Market to Book*, *Log Firm Age*, *Number of Analysts*, *Number of Deals*, *Moody Spread*, *Stock Market Return*, *Log Trades*, *Number of Bonds Outstanding*, *Duration*, *Callable, Medium Term Note, Cross Acceleration, Sale-leaseback, Change in control, Earnings Ratio, Additional Debt, and Merger restriction.* The number of observations in column (1) and (6) is lower because data on bond ownership only begins in 2000. t-statistics, using robust standard errors clustered by firm, are in brackets. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Bank Relationship	7.04	-23.11***	-3.09	-7.04	-4.48	-7.81
	(0.74)	(-3.63)	(-0.57)	(-1.24)	(-0.79)	(-0.52)
Bank Rel.× Low Concentration	-36.61**					-26.17
	(-2.56)					(-1.63)
Bank Rel.× Has Traded CDS		26.77***				27.53*
		(2.59)				(1.70)
Bank Rel.× Loan is Secured			-30.41***			13.37
			(-2.65)			(0.58)
Bank Rel.× Dividend Restriction				-17.04*		-3.80
				(-1.67)		(-0.22)
Bank Rel.× Junk					-21.06**	-11.93
					(-2.03)	(-0.56)
Low Concentration	42.46***					34.38**
	(2.82)					(2.15)
Has Traded CDS		-5.36				4.29
		(-0.41)				(0.21)
Has Dividend Restriction				9.17		6.62
				(0.96)		(0.42)
Loan is Secured	28.80**	29.09***	51.76***	30.50***	29.36***	15.49
	(2.49)	(3.91)	(4.46)	(4.06)	(3.94)	(0.71)
Observations	2386	5236	5236	5236	5236	2386
R^2	0.452	0.490	0.490	0.489	0.489	0.455
N. Issuers	873	1,139	1,139	1,139	1,139	873
Year & Rating dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table VI: Instrumental Variables Regression

This table presents IV estimates of the following system of equations:

$$\textit{Bank Relationship}_{it} = \alpha_1 + \sum_{x=1}^{X} \phi_x (\text{Bond and Loan Characteristics})_{itx} + \sum_{y=1}^{Y} \delta_y (\text{Firm Characteristics})_{ity},$$

$$\textit{Yield Spread}_{it} = \alpha_0 + \beta_1 (\widehat{\textit{Bank Relationship}})_{it} + \sum_{k=1}^{K} \psi_k (\text{Bond, Loan, and Firm Characteristics})_{itk}$$

All non-binary independent variables are standardized to have mean zero and unit variance to facilitate the interpretation of point estimates. (Bank $\widehat{\text{Relationship}}$) is estimated from the first equation using a linear probability model. Column (1) and (2) present results from estimation of the top equation, and column (3) presents estimated coefficients of the bottom equation. The instruments are *High Distance*, a dummy equals one if a firm is in the top quintile of minimum spherical distance in miles from the firm's headquarter to the headquarters of the closest loan syndicate participant, and *Low Bank Deposits*, a dummy equals one if a firm is in the bottom quintile of median bank branch deposits in the county in which the firm is located. *Other Controls*, defined in Table I, include: *Number of Deals*, *Moody Spread*, *Stock Market Return*, *Log Trades*, *Number of Bonds Outstanding*, *Callable, Medium Term Note, Cross Acceleration, Sale-leaseback, Change in control, Earnings Ratio, Additional Debt, and Merger restriction*. Robust standard errors clustered by firm, are in brackets. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Bank Relationship		Yield Spread
	(1)	(2)	(3)
High Distance	-0.13***	-0.10***	
	(-9.03)	(-6.50)	
Low Bank Deposits	-0.02	-0.03**	
	(-1.58)	(-2.17)	
Bank Relationship			-139.88***
			(-2.75)
Log Market Equity		0.02	-20.83***
		(1.21)	(-3.29)
Market Leverage		0.01	15.44***
		(0.82)	(3.25)
Profitability		0.01	-5.79**
		(0.80)	(-2.28)
Firm Equity Volatility		-0.02**	48.14***
		(-2.39)	(12.54)
Log Public debt		-0.01	-23.32***
		(-0.64)	(-7.52)
Interest Coverage		0.00	-6.38
		(0.34)	(-1.60)
Market to Book		0.01	-10.46***
		(0.66)	(-3.55)
Firm Age		0.01	-2.43
		(0.72)	(-0.87)
Number of Analysts		0.00	1.47
		(0.13)	(0.40)
Duration		0.01	7.12***
		(0.91)	(3.52)
Observations	6816	5236	5236
R^2	0.02	0.12	0.62
N. Issuers	1,429	1,352	1,352
Other Controls	No	Yes	Yes
Year and Rating dummies	No	Yes	Yes
Kleibergen-Paap rk LM			42.73
Cragg-Donald Wald F			26.41
10% Stock-Yogo critical value			19.93
Hansen J P-val			0.31

Table VII: Effect of Oil Shock by Relationship Status

This table presents estimates of the effect of the July 2014 oil shock by banking relationship status. Our sample period is July 2013 to June 2015. These regressions are run using the sample of bonds outstanding *before and after* the July 2014 Oil Shock. We also exclude financial firms (SIC 6000 – 6999) and regulated utilities (SIC 4900 – 4949). *Bank Relationship* is a dummy equal to one if over the prior five years the borrower has loans arranged by the lead bank on any of its current loans. *Buy & Hold Return* is the monthly cumulative return (%) from buying a firm's stock at the beginning of the sample period, 12 months before the July 2014 oil price decline. *Firm Characteristics, Bond & Loan Characteristics, and Indenture Covenants*, defined in Table I, include *Log Market Equity*,*Market Leverage*, *Profitability*, *Log Equity Volatility*, *Log Public debt Outstanding*, *Interest Coverage*, *Market to Book*, *Log Firm Age*, *Number of Analysts*, *Number of Deals*, *Moody Spread*, *Stock Market Return*, *Log Trades*, *Number of Bonds Outstanding*, *Duration*, *Callable, Medium Term Note, Cross Acceleration, Sale-leaseback, Change in control, Earnings Ratio, Additional Debt, and Merger restriction*Ratings Dummies* are dummies for the median bond rating of each bond, coded as 7 for AAA, 6 for AA, and so on. Standard errors are clustered by firm with t-statistics reported in parenthesis and significance represented according to: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)
Post-Oil Shock× Oil Firms× Bank Relationship		-230.37*	-254.98**	-231.63**
		(-1.92)	(-2.38)	(-2.21)
Post-Oil Shock×Oil Firms	107.91***	304.39**	281.92***	262.84***
	(4.52)	(2.54)	(2.74)	(2.60)
Post-Oil Shock	-10.24***	-6.05**	25.85***	28.57***
	(-2.71)	(-2.08)	(4.08)	(4.40)
Oil Firms	64.05**	22.40**	-3.52	-0.00
	(2.38)	(2.18)	(-0.28)	(-0.00)
Bank Relationship		9.76	10.71	9.30
		(0.83)	(0.89)	(0.76)
Buy & Hold Return			-0.84***	-0.81***
			(-4.91)	(-4.79)
Observations	52810	52810	43459	43459
R^2	0.04	0.59	0.62	0.69
Ratings dummies	No	Yes	Yes	Yes
Indenture Covenants	No	No	No	Yes
Bond & Loan Characteristics	No	No	No	Yes
Firm Characteristics	No	No	Yes	Yes
N.Issuers	554	554	387	387

Table VIII: Effect of Banking Relationships on CDS Spreads

This table presents OLS, and fixed-effects estimates of the following equation:

$$\textit{CDS Spread}_{it} = \alpha_i + \beta_1(\textit{Bank Relationship})_{it} + \sum_{j=1}^{J} \gamma_j(\text{Bond \& Loan Characteristics})_{itj} + \sum_{k=1}^{K} \nu_k(\text{Firm Characteristics})_{itk} + \lambda_t.$$

All non-binary independent variables are standardized to have mean zero and unit variance to facilitate the interpretation of point estimates. *Junk* is is a dummy equals to one if a firm's S&P senior unsecured rating is non-investment grade. *Other Controls*, defined in Table I, include: *Number of Deals*, *Moody Spread*, *Stock Market Return*, *Log Trades*, *Number of Bonds Outstanding*, *Callable, Medium Term Note, Cross Acceleration, Sale-leaseback, Change in control, Earnings Ratio, Additional Debt, and Merger restriction.* t-statistics, using robust standard errors clustered by firm, are in brackets. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	OLS		Fixed Effects	
	(1)	(2)	(3)	(4)
Bank Relationship	-40.74***	-11.37*	-3.99	9.79
	(-3.56)	(-1.73)	(-0.59)	(1.75)
Bank Relationship × Junk				-42.24**
				(-2.57)
Log Market Equity		-2.33	-7.90	-10.02
		(-0.29)	(-0.50)	(-0.63)
Market Leverage		29.93***	10.59	11.83
		(3.77)	(0.88)	(0.99)
Profitability		-1.92	-5.24	-3.97
		(-0.57)	(-0.71)	(-0.54)
Firm Equity Volatility		36.02***	28.18***	28.37***
		(8.50)	(5.32)	(5.44)
Log Public Debt		-9.44***	-17.03***	-16.94***
		(-2.85)	(-4.28)	(-4.24)
Interest Coverage		-0.91	-7.62	-7.72
		(-0.15)	(-0.97)	(-1.01)
Market to Book		-1.37	-11.54*	-11.03
		(-0.44)	(-1.72)	(-1.63)
Firm Age		-3.80	81.50*	80.86*
		(-0.93)	(1.71)	(1.72)
Number of Analysts		-2.47	6.12	4.70
		(-0.50)	(0.80)	(0.61)
Duration		-5.08***	-2.93*	-2.87*
		(-3.10)	(-1.94)	(-1.90)
Observations	1911	1591	1591	1591
R^2	0.01	0.73	0.46	0.47
N. Issuers	451	389	389	389
Issuer FE	No	No	Yes	Yes
Year and Rating dummies	No	Yes	Yes	Yes

Table IX: Effect of Banking Relationships on Yield Spreads by Data Source.

This table presents fixed effect estimates of the following equation:

$$\textit{Yield Spread}_{it} = \alpha_i + \beta_1(\textit{Bank Relationship})_{it} + \sum_{j=1}^{J} \gamma_j(\text{Bond and Loan Characteristics})_{itj} + \sum_{k=1}^{K} \nu_k(\text{Firm Characteristics})_{itk} + \lambda_t.$$

All non-binary independent variables are standardized to have mean zero and unit variance to facilitate the interpretation of point estimates. Model (1) and (4) report OLS estimates, while model (2), (3), (5), and (6) present results after including firm-fixed effects. *NAICS Sample* indicates that bond prices were obtained from the National Association of Insurance Commissioners. *TRACE Sample* indicates that bond price data were obtained from the Trade Reporting and Compliance Engine through WRDS. *Other Controls*, defined in Table I, include: *Number of Deals*, *Moody Spread*, *Stock Market Return*, *Log Trades*, *Number of Bonds Outstanding*, *Callable, Medium Term Note, Cross Acceleration, Sale-leaseback, Change in control, Earnings Ratio, Additional Debt, and Merger restriction.* t-statistics, using robust standard errors clustered by firm, are in brackets. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	NAICS Sample			Trace Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Relationship	-95.61***	-23.68**	-23.98**	-99.82***	-16.42**	-12.86*
	(-8.85)	(-2.54)	(-2.53)	(-8.71)	(-2.19)	(-1.80)
Log Market Equity		-8.86	-6.28		-21.64	-7.22
		(-0.44)	(-0.33)		(-1.37)	(-0.48)
Interest Coverage		6.09	2.33		-8.09	-5.61
		(0.51)	(0.20)		(-0.89)	(-0.62)
Market Leverage		10.27	8.70		19.27*	20.63*
		(0.74)	(0.68)		(1.71)	(1.89)
Profitability		-5.08	-7.05		3.89	2.39
		(-0.39)	(-0.56)		(0.45)	(0.30)
Number of Analysts		11.07	5.80		21.88***	17.78**
		(0.95)	(0.47)		(2.65)	(2.14)
Firm Age		150.01***	99.81*		143.32***	66.61
		(2.98)	(1.70)		(3.70)	(1.56)
Firm Equity Volatility		59.74***	49.31***		56.29***	45.86***
		(8.06)	(4.92)		(10.55)	(7.37)
Log Public debt		-30.87***	-29.37***		-33.52***	-32.64***
		(-4.87)	(-4.81)		(-5.62)	(-5.70)
Market to Book		4.15	3.38		-25.86***	-20.71***
		(0.44)	(0.39)		(-3.49)	(-2.84)
Duration		-8.80*	-6.60		17.85***	18.05***
		(-1.82)	(-1.43)		(7.52)	(7.91)
Observations	2762	1722	1722	3725	2683	2683
R^2	0.03	0.80	0.81	0.03	0.82	0.84
N.Issuers	1,214	526	526	968	609	609
Issuer FE	No	Yes	Yes	No	Yes	Yes
Year dummies	No	No	Yes	No	No	Yes
Ratings dummies	No	Yes	Yes	No	Yes	Yes
Other Controls	No	Yes	Yes	No	Yes	Yes