Nonbank Lending

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ABSTRACT

We provide novel systematic evidence on the terms of direct lending by nonbank financial institutions. Analyzing hand-collected data for a random sample of publicly-traded middle-market firms during the 2010-2015 period, we find that nonbank lending is widespread, with 30% of all loans being extended by nonbanks. Firms are more likely to borrow from a nonbank lender if local banks are poorly capitalized and less concentrated. Nonbank borrowers are smaller, more R&D intensive, and significantly more likely to have negative EBITDA. Nonbank lenders are less likely to monitor by including financial covenants in their loans, but appear to engage in more ex-ante screening: origination of nonbank loans is associated with larger positive announcement returns. We find that nonbank borrowers pay about 200 basis points higher interest rates than bank borrowers. Using fuzzy regression discontinuity design and matching techniques generates similar results. Overall, our results provide evidence of market segmentation in the commercial loan market, where bank and nonbank lenders utilize different lending technologies and cater to different types of borrowers.

Keywords: shadow banking, relationship lending

JEL Classification: G21, G23, G30, G32

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1 Introduction

Who supplies credit to U.S. firms has been an important question recently due to increased bank capital requirements and the growth of the shadow banking system (Chen et al 2017, Plantin 2014). While there have been anecdotal reports of hedge funds and other nonbank financial intermediaries lending to small and medium-sized businesses,[1] there is little systematic evidence on the direct lending by nonbank lenders to such businesses. This paper provides novel systematic evidence on the sources and terms of private debt financing during the post crisis period.

We construct a hand-collected data set of credit agreements signed between 2010 and 2015 by a random sample of publicly-traded middle market firms. Defined as firms with revenues between $10 million and $1 billion, middle market firms account for about one third of all U.S. jobs and of private sector GDP.[2] Since larger firms are more likely to have credit ratings and therefore access to market-based financing (Faulkender and Petersen 2005), middle market firms are more likely to be affected by the availability of bank versus other forms of single-lender, private debt financing. We focus on publicly-traded firms with at least $10 million in revenue because our data on loan contract terms come from SEC filings. Thus, our data do not capture very small firms borrowing through peer-to-peer lending platforms. At the same time, focusing on somewhat larger firms allows us to study the price and non-price terms offered by different types of lenders.

Our first result is to document the prevalence of direct lending by financial intermediaries other than commercial banks, for short, nonbank lending. Such lending is widespread: About one third of all commercial and industrial loans taken out by publicly-traded middle market firms during the 2010-2015 period is extended by nonbank lenders. These lenders represent a variety of financial institutions including finance companies (FCOs), private equity/venture capital (PE/VC) firms, hedge funds, bank-affiliated finance companies (bank FCOs), investment banks, insurance companies, business development companies (BDCs), and investment managers. Strikingly, we

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[1] See, for example, Ahmed (2011), Griffiths (2011), and Carley (2010).
[2] National Center for the Middle Market info sheet http://www.middlemarketcenter.org/Media/Documents/NCMM_InfoSheet_2017_web_updated.pdf

find that even for publicly traded firms, standard databases such as DealScan cover only a fraction of bank loans and almost none of the loans that are extended directly by nonbank lenders.

After establishing the prevalence of nonbank lending, we explore the characteristics of firms that borrow from nonbank lenders versus banks. Compared to firms that borrow from banks, nonbank borrowers are smaller, younger, more R&D intensive, and more likely to report negative EBITDA. Thus, contrary to received wisdom, banks do not appear to be special in lending to firms that require significant screening and monitoring. Profitability is a particularly important driver of the choice of lender. Firms with small negative EBITDA are about 40% more likely to borrow from a nonbank lender than are firms with small positive EBITDA. This finding is consistent with banks finding it costly to lend to unprofitable firms since such loans are classified as substandard.

The discontinuity in the probability of borrowing from a nonbank lender around zero EBITDA allows us to implement a fuzzy regression discontinuity design (fuzzy RDD) to estimate the causal effect of borrowing from a nonbank lender on various price and non-price terms. While the average difference in interest rates between bank and nonbank loans, controlling for observable firm characteristics, is around 200 basis points, this difference is about 480 basis points at the zero EBITDA threshold. This difference in interest rates is likely driven by partial market segmentation and nonbank lenders facing higher cost of funding than cheap deposits that banks have access to. We also find evidence that lenders try to match the interest rate exposure of their assets and liabilities, with nonbanks being much more likely to offer fixed-rate loans (Kirti 2017).

According to our RDD analysis, nonbank loans are 45% less likely to include financial covenants. Instead of ex-post monitoring through financial covenants, which may be difficult to set accurately for young, R&D-intensive firms, nonbanks try to align incentives through the use of warrants and engage in significant ex-ante screening. We find that origination of nonbank loans is associated with significantly higher positive abnormal announcement returns than origination of bank loans. The results on contract terms and announcement returns suggest that bank and nonbank lenders may utilize different lending techniques. While banks appear to rely more heavily on ex-post monitoring through financial covenants, nonbank lenders may rely more on ex-ante screening and alignment of incentives.

Nonbank lenders' greater reliance on ex-ante screening could also help explain the difference in interest rates between bank and nonbank loans. Since information generated in the course of ongoing monitoring after loan origination can be used to hold-up borrowers, lenders that rely on ex-post monitoring may smooth interest rates over time, setting lower interest rates initially and not decreasing them much over time (Petersen and Rajan 1995). Lenders that screen ex-ante but do not monitor as much ex-post will charge higher initial interest rates. Such lenders may also charge higher upfront fees to compensate them for the fixed costs of initial screening. Indeed, we find that nonbank loans charge 26 basis points higher upfront fees than bank loans.

We also explore whether there are any differences in the ex-post performance of loans originated by bank versus nonbank lenders. While in univariate regressions, firms that borrow from nonbank lenders are significantly more likely to file for bankruptcy within three years of loan origination, this difference is driven by such firms being riskier on observable characteristics such as EBITDA. Controlling for firm characteristics, nonbank borrowers are not more likely to file for bankruptcy than bank borrowers. We find similar results when looking at changes in profitability after loan origination.

In our final analysis, we relate the propensity to borrow from nonbank lenders to the conditions in the firm's local banking market. We find that if banks with branches in a given county are better capitalized, firms headquartered in that county are less likely to turn to nonbank lenders for funding. Although our tests do not provide causal evidence, the strength of the relation is economically important. A one percentage point increase in the tier 1 leverage ratio of such banks is associated with a 5-8% decline in the probability of borrowing from a nonbank lender. Our results point to the importance of local credit supply shocks not only for small private-held firms, as shown by Chen, Hanson, and Stein (2017), but also for medium-size publicly traded firms.

We also find that concentration of the local banking market is negatively correlated with the probability of borrowing from a nonbank lender. An increase in the HHI of local deposit concentration of 0.10 is associated with a 3-4% decline in the probability of borrowing from a nonbank lender. Our results are consistent with the recent theoretical model of Donaldson, Piacentino, and Thakor (2017). In their model, nonbanks' higher cost of capital acts as a commitment device to lend only to innovative firms. When bank competition is weak, banks internalize the benefits of lending to and monitoring innovative firms, leaving less room for nonbanks to enter. When bank competition is strong, on the other hand, banks lend to safe firms at a low cost, while nonbanks lend to riskier, more innovative firms.

Overall, our results are consistent with differences in funding stability and in reliance on ex-ante screening versus ex-post monitoring across lender types driving the matching process between borrowers and lenders as well as the actual loan terms. Except for insurance companies who have stable long-term funding and who lend at long maturities, the other nonbank lenders in our data, hedge funds in particular, tend to rely on less stable, shorter term funding. To better match the maturity of their liabilities, these nonbanks lend at shorter maturities to borrowers that due to asymmetric information and moral hazard considerations cannot borrow long-term (Diamond 1991). Importantly, with the exception of insurance companies, differences in maturity across lender types largely disappear once we control for firm characteristics. Thus, maturity appears to be primarily determined by firm fundamentals, with lenders and borrowers matching based on what would be the optimal debt maturity for a given borrower.

Our paper contributes to a growing literature on the role of the shadow banking system in providing credit to firms. While a number of papers have looked at the participation by nonbank financial intermediaries in loans arranged and syndicated by banks (Lim, Minton, and Weisbach (2014), Nadauld and Weisbach (2012), Ivashina and Sun (2011), Massoud et al. (2011), and Jiang, Li, and Shao (2010)), and on sales of loans by banks to nonbanks (Irani et al. 2017), there is less work on nonbanks lending directly to firms. Most of the loans made to middle-market firms are direct loans rather than tranches in syndication structures. Therefore, it is important to understand the role of direct lending by nonbank institutions in the credit markets for a typical firm. Chen, Hanson, and Stein (2017) show that following the pull-back by the top 4 banks from small business lending in the midst of the financial crisis, nonbank finance companies and online lenders have been filling the void in the small business lending market. Compared to Chen, Hanson, and Stein (2017) our data cover larger firms and allow us to study the characteristics of firms that borrow from different types of lenders as well as the price and non-price contract terms.

In focusing on the source of incremental debt financing, our paper is related to Denis and Mihov (2003) who study firms' decision to issue public bonds, borrow from banks or from nonbank private lenders. They find that firms with the highest credit quality borrow from public sources while firms with the lowest credit quality borrow from nonbank private lenders. Their sample of private nonbank debt consists of larger issues with longer maturities and is therefore quite different from our sample covering the post crisis period. Furthermore, Denis and Mihov (2003) do not know the identity of private nonbank lenders, which we show to be an important determinant of lending terms. In particular, lending by insurance companies, who were the main source of private nonbank debt financing in the 1980s and 1990s, looks very different from other types of nonbank loans.

Using DealScan data, Kim, Plosser, and Santos (2017) show that after US regulators issued interagency guidance on leveraged lending in 2013, nonbanks increasingly acted as lead arrangers in the syndicated loan market, while funding themselves through bank loans. Carey et al. (1998) also use DealScan data to study loans arranged by banks versus finance companies and find that the latter tend to lend to observably riskier borrowers. Our paper studies other types of nonbank lenders, including hedge funds, PE/VC firms, and investment managers, covers the more recent period, and includes many nonsyndicated loans that are not included in the DealScan database. Agarwal and Meneghetti (2011) examine the characteristics of firms that borrow from hedge funds as well as the stock price reactions around loan announcements. Their sample, however, consists of 44 loans during the 1999-2006 period and thus cannot speak to the systematic importance of nonbank lending during the recent period.[3] In contrast to Agarwal and Meneghetti (2011), our data on contract terms allows us to compare the terms of lending across different lender types and speaks to the differences in lending technologies utilized by bank and nonbank lenders.

The rest of the paper is organized as follows. Section 2 introduces our sample, discusses the data collection process, and presents summary statistics. Section 3 compares the characteristics of firms borrowing from different types of lenders. In Section 4, we analyze differences in both price and non-price term between bank and nonbank loans. We also present our results utilizing a fuzzy regression discontinuity design well as matching techniques. Section 5 explores the ex post performance of loans in our data, while Section 6 relates the propensity to borrow from nonbank lenders to the conditions in the local banking markets where borrowers operate. Section 7 concludes.

[3] Agarwal and Meneghetti (2011) select loans that received press coverage due to being extended by hedge funds.

2 Sample construction and summary statistics

We now describe our sample construction and provide summary statistics on borrowers and loans in our data.

2.1 Sample construction

With the exception of investment banks and a small number of finance companies, nonbank lenders generally do not report their commercial loans to providers of standard databases such as DealScan or Leveraged Commentary and Data (LCD). As a result, our loan data are largely hand collected and supplemented with DealScan whenever loans are in fact reported in DealScan.

Our sample consists of a random sample of 632 publicly-traded US-based middle market firms that appear in Compustat at least once during the 2010-2015 period.[4] Following the definition used by the National Center for the Middle Market, we define middle market firms as firms with revenues between \$10 million and \$1 billion.[5] Unlike EBITDA-based definitions typically used by lenders in the leveraged loan market, this revenue-based definition allows us to include unprofitable firms in the analysis. Consequently, our sample is a more heterogeneous and representative set of mid-sized publicly traded firms than one could obtain from extant databases that typically focus on the leveraged loan market. To focus on firms that are likely to have entered into significant debt contracts, we require our firms to report book leverage of at least five percent at some point during the 2010-2015 period. Financial firms and utilities are excluded.

Regulation S-K requires firms to file material contracts, including loan and credit agreements, as exhibits to the SEC filings. We obtain lists of debt related agreements from Capital IQ. Because Capital IQ's coverage of key documents has improved over time, we focus on a recent sample of debt contracts filed between 2010 and 2015. We exclude documents related to bonds underwritten by investment banks and placed with multiple investors, but retain all other debt contracts such as lines of credit, term loans, and promissory notes. To avoid capturing minor renegotiations and maturity extensions, we restrict our sample to original contracts as well as

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[4] Our initial sample consists of 750 firms, but we are still coding contracts for the remaining 118 firms. More detailed discussion of sample construction and data extraction can be found in Appendix A.
[5] http://www.middlemarketcenter.org

amended and restated agreements. We exclude simple amendments, covenant waivers, and joinder agreements.

To economize on manual data collection, we first attempt to match all contracts to DealScan based on the identities of the borrowers, lead lenders, and origination dates. About 42 percent of the final sample contracts can be found in DealScan. Note that our sample includes bank loans and about 85 percent of the DealScan-matched contracts are bank loans, for which the match rate is still only 52 percent of the total number of bank loans in our sample. For matched contracts, we extract loan characteristics from DealScan. For the remaining contracts, we read the credit agreements and record their characteristics, including amount, maturity, interest rate, fees, priority, security, convertibility, the presence of financial covenants, performance pricing, or warrants, and the tranche structure if it exists. Interest rates are recorded as follows. For fixed-rate instruments, we record the interest rate as stated in the contract. For floating-rate instruments, we record the spread over the London Interbank Offered Rate (LIBOR).[6] We also calculate the loan's initial interest rate as either the fixed rate specified in the contract or the level of LIBOR as of the origination date plus the stated spread. If a contract stipulates an interest rate floor, we use the greater of the calculated interest rate and the floor. Appendix A provides more detail on sample construction and coding of credit agreements.

To understand what type of firms borrow from what type of nonbank lenders and how contract terms vary with this choice, it is important to determine each lender's type. We rely on lenders' descriptions in Capital IQ as well lists of business development companies (from Capital IQ), private equity funds (from Preqin), and hedge funds (from SEC form ADV). We search for the remaining lenders in Capital IQ and read their business descriptions. If the lender is an individual, a nonfinancial corporation, or a government entity, we exclude the contract from the sample.[7] Syndicated loans are classified according to the identity of the lead arranger.

We measure borrower characteristics as of the quarter preceding loan origination. For balance sheet variables, we use the most recent quarterly data, while income and cash flow

[6] Whenever the contract allows the borrower to choose between several base rates, most commonly LIBOR and prime, we record the spread over LIBOR. In about 13% of the loans, the contract provides for a different base rate such as the bank's prime rate. We convert spreads over such alternative base rates into a spread over LIBOR.
[7] Nonfinancial lenders primarily represent seller financing and intercompany loans.

statement items are calculated on a trailing twelve months basis. Borrower financials, as reported in the original filings and thus seen by lenders at the time of loan origination, are from Capital IQ. A detailed description of all variables used in the analysis can be found in Appendix B. All financial ratios are winsorized at the 1st and 99th percentiles. Because our sample includes many relatively small firms, winsorization does not remove all outliers. To deal with this problem, we cap the ratios of debt to assets and research expense to assets as well as sales growth and the level and change in the ratio of EBITDA to assets at a value of one. The final sample consists of 1,035 debt contracts entered into by 471 borrowers.

2.2 Summary statistics

Panel A of Table 1 reports the number of bank and nonbank loans taken out by our sample firms during the 2010-2015 period. Observations are reported at the deal level, rather than at the tranche level as syndicated loans frequently have multiple tranches. Nonbank lenders extend almost one third of all loans in our data. Panel B shows the different types of nonbank lenders in our sample: finance companies (FCOs), bank finance companies (bank FCOs), investment banks, insurance companies, business development companies (BDCs), private equity (PE) and/or venture capital (VC) funds, hedge funds, investment managers, and others.[8] FCOs (26%), PE/VC firms (19%), and hedge funds (17.5%) account for the largest share of nonbank lending in our sample. An important note to emphasize from Table 1 is that only 20% of nonbank loans are tracked in DealScan. In particular, DealScan rarely covers loans extended by asset managers.[9]

3 Who borrows from nonbanks?

In this section, we explore the characteristics of firms that borrow from bank versus nonbank lenders. Table 2 reports the means and standard deviations of various firm and loan characteristics for nonbank and bank loans. The rightmost column reports the difference in means between nonbank and bank loans along with the *t*-statistic that allows for unequal variances across the two groups. We aggregate across multiple tranches within each deal and report one observation per deal.

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[8] Others include collateralized loan obligations, mutual funds and real estate investment trusts.
[9] We also checked whether nonbank loans show up as private placements in SDC. The vast majority of nonbank loans in our data do not appear to be included in SDC.

Nonbank borrowers are significantly smaller than bank borrowers in terms of their book assets and EBITDA. The average nonbank borrower has book assets of $324 million and EBITDA of $21 million. The average bank borrower has book assets of $596 million and EBITDA of $72 million. Figure 1 further emphasizes the importance of EBITDA in determining lender type. We sort firms into twenty equal-sized bins based on their trailing twelve-month EBITDA at the time of loan origination and report the fraction of loans in each bin extended by nonbanks. The fraction of loans originated by nonbanks drops sharply from around 60% to the left of zero EBITDA to around 20% to the right of zero EBITDA. We will use this jump later on in our fuzzy regression discontinuity analysis.

Compared to bank borrowers, firms that borrow from nonbanks are younger (29 vs. 38 years), spend a larger fraction of their assets on R&D (9% vs. 4%), and have higher market-to-book ratios (1.70 versus 1.58). Nonbank borrowers experience greater stock return volatility.

Along with being smaller, nonbank borrowers get smaller loans ($72.5 vs. $185 million), but report higher leverage prior to loan origination (38% vs. 26%) than bank borrowers. The interest rate on nonbank loans is almost 500 basis points higher than the interest rate on bank loans, although the results above suggest that part of this difference is due to nonbank borrowers being riskier. Interestingly, nonbanks loans are less likely to include financial covenants or performance pricing, but they are significantly more likely to use warrants and convertible debt.

We next turn to multivariate regression analysis of the characteristics of bank and nonbank borrowers. Table 3 reports estimates from a linear probability model of borrowing from a nonbank lender. The effect of firm size is negative but not statistically significant in three of the four specifications. EBITDA and negative EBITDA in particular are more important determinants of whether a firm borrows from a nonbank lender. Consistent with the results in Figure 1, the effect of EBITDA is driven largely by whether a firm has positive EBITDA. While the existing literature shows that less profitable firms are more likely to borrow from finance companies (Carey et al 1998), hedge funds (Agarwal and Meneghetti 2011), and other nonbank private lenders (Denis and Mihov 2003), it does not emphasize the importance of positive EBITDA, which in our data is the most important determinant of borrowing from a nonbank lender. The importance of positive EBITDA for bank lending is consistent with banks lacking expertise in maximizing the value of collateral and therefore relying on cash flow as the principal source of loan repayment.

Furthermore, banks may be reluctant to extend loans to firms with negative EBITDA because such loans would be rated “substandard.”[10]

Higher leverage is consistently associated with a significantly higher probability of borrowing from a nonbank lender. A 10% increase in leverage is associated with about 4% increase in the probability of borrowing from a nonbank lender. While the effect of R&D is statistically significant in column 1, it is cut in half and is no longer statistically significant once we control for the negative EBITDA dummy in columns 2-4.

In column 3, we add controls for receivables and inventories – two categories of assets commonly used in secured lending. The marginal effect of inventories (as a share of total assets) is negative and large economically: a one standard deviation increase in inventories of 17% is associated with almost 5% reduction in the probability of borrowing from a nonbank.

Finally, column 4 adds borrower fixed effects. Although we do not have as much within borrower as cross borrower variation, we continue to find that when the same firm has negative EBITDA or higher leverage, it is much more likely to borrow from a nonbank lender. Within firm, there is marginal evidence that borrowers with low market-to-book ratios are more likely to borrow from nonbanks.

So far we have treated all nonbank loans as being similar, but there could be important differences in the characteristics of firms that borrow from different types of nonbank lenders. To investigate matching between firms and different types of nonbank lenders, Table 4 estimates multinomial logit regressions predicting lender type. We present the results of three models, with bank loans being the base outcome in all three. Where the models differ is in how they aggregate lender types into larger groups.

In model 1, the four outcomes are 1) borrowing from an independent finance company or a bank-affiliated financed company, 2) borrowing from an investment bank, 3) borrowing from an insurance company, and 4) borrowing from a business development company, private equity, venture capital, hedge fund, or other investment manager. We refer to this last outcome as borrowing from an asset manager. Compared with bank borrowers, firms borrowing from FCOs,

[10] OCC Comptroller’s Handbook on Rating Credit Risk: https://www.occ.treas.gov/publications/publications-by-type/comptrollers-handbook/rating-credit-risk/pub-ch-rating-credit-risk.pdf

investment banks, or asset managers are more likely to have negative EBITDA and higher leverage. Borrowers from asset managers are on average smaller; however, borrowers from investment banks are on average larger than bank borrowers. Firms that borrow from insurance companies stand out in having high values of PPE and spending little on R&D. These results are consistent with insurance companies lending to firms with long duration assets in an effort to match the long duration of insurance policies.

Model 2 separates bank FCOs and unaffiliated FCOs, and Model 3 separates hedge funds and investment managers from other types of asset managers.[11] Bank FCOs and unaffiliated FCOs are similar in their lending preferences, with one exception. Negative EBITDA has a larger and statistically significant coefficient for unaffiliated FCOs but not for bank FCOs. In model 3, we split asset managers into two groups: 1) business development companies, private equity, and venture capital, and 2) hedge funds and investment managers. Model 3 uncovers some interesting differences among these lenders. Highly levered firms are significantly more likely to borrow from hedge funds and investment managers than from business development companies, private equity, or venture capital (Wald test *p*-value for difference in relative risk ratios: 0.048). The latter group is more likely to lend to firms that engage in a lot of R&D (*p*-value: 0.080) and have higher sales growth (*p*-value: 0.010). Firms that borrow from hedge funds and investment managers, on the other hand, do not appear to spend more on R&D than bank borrowers. The difference in R&D intensity between firms that borrow from BDC, PE, and VC firms versus hedge funds could be explained by the former having access to more stable funding and thus having longer investment horizons than hedge funds. BDC and VC firms could also be more skilled in evaluating R&D intensive firms.

4 Differences in contract terms

Univariate comparisons in Table 1 suggest significant differences in both price and non-price terms of bank versus nonbank loans. Nonbank loans, for example, charge significantly higher interest rates. Some of these differences in contract terms are likely due to differences in the

[11] In the Internet Appendix, we perform cluster analysis on our sample loans and find strong separation of bank-like loans from loans made by asset managers. FCOs and bank FCOs straddle both. We also examine which of the asset managers are most similar to each other in their lending behavior. This allows us to subsume investment managers and BDCs, both of whom have few observations, into larger groups. As the internet appendix shows, investment managers are most similar to hedge funds, and BDCs are most similar to PE/VCs.

characteristics of firms that borrow from bank versus nonbank lenders. In particular, as we just saw, firms that borrow from nonbanks are less likely to be profitable. The question we ask in this section is whether differences in contract terms persist once we control for firm characteristics. In other words, when firms that are similar on observable characteristics borrow from different types of lenders, do they obtain similar or different terms?

4.1 Interest rate

In table 5, we present the results of the analysis of the initial interest rate charged on bank versus nonbank loans. Initial interest rate is set to the fixed interest rate for fixed rate loans and to the current value of the one-month London Interbank Offered Rate (LIBOR) plus the applicable spread for floating rate loans. Because other loan terms are determined simultaneously with the interest rate, we present the results with and without loan level controls. We include the following firm level controls: log total assets, profitability (EBITDA divided by total assets), leverage, research expense, property, plant & equipment (PP&E), cash, receivables, inventory ratios, and log firm age as well as volatility, growth, and market-to-book ratio in some specifications.

Column 1 presents univariate comparison of the interest rates charged on nonbank versus bank loans. The difference of 481 basis points is large and highly statistically significant. Once we add firm level controls in column 2, the coefficient on the nonbank dummy is reduced to 365 basis points. The coefficients on firm characteristics are consistent with theory. Larger and more profitable firms pay significantly lower interest rates. A ten percentage points reduction in profitability is associated with a 23 basis points higher interest rate. Firms that have lower leverage or more receivables also pay significantly lower interest rates. A ten percentage points decrease in leverage or increase receivables is associated with 16-21 basis points lower interest rate.

In column 3 we add controls for other loan terms: amount, performance pricing, seniority, security, etc. The coefficient on the nonbank dummy is reduced further from 365 basis points to 223 basis points, suggesting that a large part of the difference in the interest rates charged on bank versus nonbank loans to firms with similar observables is due to differences in the types of loans extended by different lenders. Nonbank loans are significantly more likely to be junior or second lien loans and to charge fixed rates. All of these features are associated with higher interest rates.

At the same time nonbank loans are less likely to include performance pricing provisions which are associated with lower initial interest rates.

Adding the upfront fee and annual fee in column 4 has little effect on most of the coefficients. The main exception is that the coefficient on performance pricing is reduced by half from 59 to 37 basis points. Since the upfront and annual fees are expressed in basis points, the interpretation of their coefficients is that a 10 basis points higher upfront or annual fee is associated with 7-9 basis points higher interest rates. Thus, rather than being a substitute for higher interest rates, the presence of upfront and annual fees suggests riskier loans.[12]

Column 5 controls for the volatility of borrowers' stock returns.[13] Besides reducing the coefficient on the nonbank dummy further to 187 basis points, the main effect of controlling for volatility is to reduce the magnitude of the coefficients on convertible debt and especially warrants, indicating that these are more likely to be included in loans extended to firms with more volatile stock returns.

In columns 6 and 7, we decompose the effect of nonbank lending into different lender types. Controlling for firm and loan characteristics, there is no difference in the pricing of loans by banks versus bank-affiliated finance companies or insurance companies. Independent finance companies and investment banks charge about 168-194 basis points higher interest rates, while various types of asset managers charge about 400-413 basis points higher interest rates. Finally, in column 8 we include borrower fixed effects to control for time-invariant unobserved heterogeneity. The difference in interest rates between bank loans and nonbank loans increases to 292 basis points.

In unreported analysis, we explore whether simultaneous equity ownership could explain differences in interest rates (Lim, Minton, and Weisbach 2014). Using Capital IQ, we gathered information on each borrower's top 25 holders as of the quarter preceding loan origination. Matching these equity holders with our nonbank lenders, we find that significant equity ownership in borrowing firms by our nonbank lenders is rare. In only 5.79% of the nonbank loans is the lender

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[12] See Berg, Tobias, Anthony Saunders, and Sascha Steffen (2015) for a recent discussion of importance of fees in loan contracts.

[13] To ensure that volatility is unaffected by the loan contract negotiation process, we measure volatility over twelve months ending 120 days before loan origination.

a blockholder with 5% or larger stake. Hence these lenders are unlikely to affect the decision on interest rates charged or relationships in general with these borrowers.

4.2 Non-price terms

While we already touched on how differences in non-price terms explain some of the difference in interest rates between bank and nonbank loans, we now turn to a more systematic examination of the non-price terms. Table 6 reports the results of OLS regressions of various non-price terms on lender type dummies. We once again present the results with and without firm controls to show how much of the difference in lending terms is due to matching between firms and lender types.

Panel A explores basic non-price terms such as amount, maturity, and seniority. According to the results in column 1, loans by asset managers are significantly smaller than loans by banks or other nonbank lenders. Loans by finance companies, both bank affiliated and independent ones, are smaller than bank loans but larger than loans by asset managers. Investment banks extend particularly large syndicated loans. Naturally, firm size and leverage are important determinants of differences in loan size. Controlling for these and other firm characteristics, we find that the difference in coefficients between finance companies and asset managers almost disappears and converges to about -0.50.

In columns 3 and 4 the dependent variable is maturity. Loans by asset managers have 0.5-0.9 year shorter maturity, but this is entirely due to asset managers lending to small, unprofitable firms. Thus given their less stable funding, asset managers, hedge funds in particular, lend to firms for which short-term debt is likely to provide more discipline and thus be more optimal than long-term debt. Consistent with insurance companies having very stable funding, loans by insurance companies have 5 years longer maturity. This is true even when we control for firm characteristics. The coefficient on profitability, measured as EBITDA/Assets, indicates that a 10% improvement in profitability is associated with about one month longer maturity. Investment banks appear to syndicate longer maturity loans, even controlling for firm size and profitability. Column 5 and 6 indicate that nonbank loans are 16-50% less likely to be senior after controlling for firm characteristics. As shown in column 8, there is little difference in collateral requirements across lenders, except for hedge funds and investment managers.

In Panel B we turn our attention to what we refer to as performance-related non-price terms: presence of financial covenants, performance pricing, warrants, and convertible features. With the exception of insurance companies, nonbank loans are significantly less likely to include financial covenants than bank loans. This is especially the case for loans by asset managers which are 46-57% less likely to include financial covenants. Given that these lenders lend to riskier borrowers, it is somewhat surprising that they do not include financial covenants. It may be the case that nonbank loans are less likely to include financial covenants because these loans are junior to bank loans that do include financial covenants (Park 2000, Rauh and Sufi 2010). However, in unreported analyses, we find very similar effects of lender type dummies on financial covenants when we restrict the sample of loans to senior secured loans and to firms that during our sample period borrow exclusively from banks or nonbanks. Thus even when nonbanks act as senior lenders and do not rely on monitoring by banks, they are less likely to include financial covenants in their credit agreements.

Part of the explanation behind negative coefficients for asset managers is that loans to firms with negative EBITDA are less likely to have financial covenants. This may be due to standard EBITDA and EBIT based covenants not being particularly meaningful for unprofitable firms. Rather than rely on ex-post monitoring through financial covenants, asset managers may engage in more ex-ante screening to identify creditworthy borrowers. Announcement return evidence in Section 5.2 is consistent with this idea.

Panel B also shows that FCOs, investment banks, and asset managers are about 20-26% less likely than banks to use performance pricing in their loans. It is worth noting that financial covenants are almost a necessary condition for performance pricing: less than 4% of all loans with performance pricing do not report having any financial covenants.

All nonbanks, including bank affiliated FCOs, are significantly more likely than banks to use warrants. Convertible debt is also used more frequently by most nonbanks, although we do not find any loans with a convertibility feature made by bank FCOs. Both the use of warrants and convertibility appear strongly driven by the types of firms nonbanks lend to. Adding firm characteristics reduces the size of most coefficients although they remain statistically significant.

Finally, Panel C of Table 6 examines other loans terms: whether the loan is fixed rate or floating, presence of upfront and annual fees, and whether or not the loan is secured by a second lien. It is interesting that except for larger firms being less likely to borrow at fixed rates, perhaps because they are better positioned to bear interest rate risk, the choice of fixed versus floating rates is driven exclusively by lender type and not by firm characteristics. The fact that nonbank loans are significantly more likely than bank loans to be fixed rate is consistent with banks relying on floating-rate funding and matching the interest rate exposure of their assets and liabilities (Kirti 2017).

Turning to the upfront fees in columns 3 and 4, finance companies and investment banks charge 31 and 68 basis points higher upfront fees. About one third of the effect for finance companies is explained by the characteristics of firms they lend to; controlling for size in particular reduces the coefficient on the finance company dummy from 31 to 22 basis points and reduces its statistical significance. The coefficient on investment banks is only marginally affected by adding firm controls. There are no significant differences in terms of the propensity of different lender types to charge annual fees, except for PE funds, VCs and BDCs. It is worth noting though that average annual fees are very small in our data: 4 basis points for nonbank loans and 2 basis points for bank loans. Finally, FCOs, investment banks, and PE/VC firms are marginally more likely than banks to make loans secured by a second lien.

4.3 Fuzzy regression discontinuity design (RDD) around zero EBITDA

While the analyses in Tables 5 and 6 control for observable firm characteristics, there could be unobservable differences between firms that borrow from banks versus nonbanks and it could be these differences in unobservable characteristics that are driving differences in price and non-price terms across loans extended by different lenders. To estimate the causal effect of borrowing from a nonbank lender, we use fuzzy regression discontinuity design taking advantage of differences in lending models across banks and nonbanks. The traditional bank lending model requires that there be "two ways out" of a loan. This model comes in two flavors. In a cash flow loan, the bank will base its lending decision on the prospective borrower's past cash flows (typically EBITDA) as a predictor of the firm's ability to meet its debt service obligations. The second way out is the value of the collateral the borrower can provide. In contrast, an asset-based loan provides a line of credit under which borrowing is limited to a percentage of certain easily accessed collateral, such as inventory or accounts receivable. Although an asset-based loan puts less emphasis on cash flows and is thus suitable for firms with low EBITDA margins, cash flows will typically still provide the second way out. A firm that has negative cash flow will find it much more difficult to borrow from a bank.

Regulatory hurdles further constrain banks' ability to lend to negative cash flow borrowers even if they wanted to. The Interagency Guidance on Leveraged Financing of 2001 and the Interagency Guidance on Leveraged Lending of 2013 both emphasize the importance of cash flows in making lending decisions. The guidance of 2001 takes an adverse view towards credits to borrowers that have insufficient cash flow to meet their debt service obligations. The guidance of 2013 tightens this view by imposing a hard limit of 6.0 for the Debt/EBITDA ratio, above which a loan "raises concern". Naturally, a firm with negative cash flows cannot meet any of these definitions. In sum, we expect that the probability of nonbank lending should jump as cash flows become negative. This jump is apparent in Figure 1.

Internet Appendix Figure A3 shows that the discontinuity continues to be there as we zoom in closer to the neighborhood around zero EBITDA. To formally test for the existence of a discontinuity in the probability of borrowing from a nonbank lender, we follow Gelman and Imbens (2014) in using local linear polynomials of EBITDA. Appendix Table A4 reports the results for neighborhoods of \$100, \$50, \$25, \$10, and \$5 million around zero EBITDA. We consistently find that firms with negative EBITDA are 33-47% more likely to borrow from a nonbank than firms with positive EBITDA.

We check whether there are any other firm characteristics, such as firm size, age, or research expenses, that change around zero EBITDA, and do not find any consistently significant jump in any other covariate except for cash holdings, which are arguably driven by cash flows. A common concern with regression discontinuity designs is the possibility that firms could manipulate the running variable, in our case EBITDA, that determines assignment to treatment. Note however that what is important for identification is not whether agents have some control over the running variable but whether they can *precisely* manipulate it (Lee and Lemieux 2010). As long as firms cannot precisely manipulate their EBITDA, assignment to treatment is locally randomized around zero EBITDA (Lee and Lemieux 2010). To alleviate the concern that firms may be able to precisely manipulate their EBITDA, Figure 2 shows the histogram of EBITDA with a bin width of $1 million. The mode of EBITDA is just below zero, with fewer observations just above zero, contrary to what one would expect if firms were manipulating their EBITDA. Visually, the distribution appears smooth around zero. In the Internet Appendix, we use local polynomial density estimation following Cattaneo, Jansson, and Ma (2017) to formally test for a discontinuity in the EBITDA distribution. The test fails to reject the null hypothesis that the distribution is smooth.

Having shown that zero EBITDA allows us to utilize a fuzzy regression discontinuity design, we now present the results for the causal effect of borrowing from a nonbank lender on various loan terms using zero EBITDA as an instrument for nonbank lending. Table 7 uses the nonparametric estimation methodology of Calonico, Cattaneo, and Titiunik (2014) to estimate treatment effects. The optimal neighborhood bandwidth is chosen using the coverage error-rate (CER)-optimal bandwidth selector (Calonico, Cattaneo, and Farrell, 2017), which is more conservative than traditional mean squared error bandwidth selectors. Because the bandwidth selector uses the structure of all the data, it needs to be re-estimated for each outcome variable. Internet appendix Table A6 shows that the results are robust to using ad-hoc neighborhoods around zero EBITDA. The optimal bandwidth around zero EBITDA for the initial interest rate as the outcome variable is [-28.7, 28.7]. In the second stage, we find an interest rate differential of 480.6 basis points with a z statistic of 4.37. The reason this difference is larger than the coefficient on the nonbank lender dummy in Table 4 is that RDD focuses on the interest rate differential right below and above the zero-EBITDA boundary. Figure 3 plots the initial interest rate for bank versus nonbank loans to firms with different values of EBITDA. The difference in interest rates shrinks as EBITDA increases.

Nonbank loans are 45 percentage points less likely to include financial covenants but 38 percentage points more likely to include warrants. These differences are again somewhat larger than the ones in the OLS regressions of Table 6. Although it is not statistically significant, there is some evidence that nonbank loans have shorter maturity (1.5 years).

Table 7 also shows that there is no difference in the probability of bankruptcy between nonbank borrowers and bank borrowers, despite the fact that the identification strategy involves unprofitable borrowers. In addition, nonbank borrowers do not underperform bank borrowers in terms of changes in profitability. If anything, there is slight outperformance at the three-year horizon. We will revisit ex-post performance for the entire sample in section 5.

Overall, by not including financial covenants in their loans, nonbank lenders provide borrowers with greater flexibility, but impose discipline through shorter maturity and align incentives through the inclusion of warrants.

4.4 Matching results

Given the difference in EBITDA for borrowers from banks and nonbank institutions, we also employ matching techniques to create good covariate balance in our sample across borrowers from nonbanks (*treated*) and banks (*control*). To construct our *control* sample, we use Mahalanobis matching with exact matching for loan origination year in addition to nearest-neighbor matching on borrower's profitability and leverage.

Imbens and Rubin (2015) suggest using mean differences normalized by the standard deviation and the variance ratios to examine covariate balance. In Panel A of Table 8, we provide these statistics for the 'raw' and matched sample for matching conducted for the first column of Panel B, where we report matching results for the interest rate on the loan. The raw sample is the sample of treated and non-treated observations before matching is performed.

The first two columns in Panel A report differences in means that are standardized by the subsample standard deviations. A well-balanced sample would have these values close to zero. Statistics for the raw sample suggest that there is little balance in the borrower size, profitability, or leverage. After matching, the balance improves significantly with the difference of means approaching zero. The last two columns in Panel B provide variance ratios for the two subsamples. A well-balanced sample would have these values close to one. Statistics for the raw sample again suggest that there is little balance for firm size, profitability, and leverage in addition to some other firm level variables such as research expense, cash, and inventories. The matched sample, however, is much better balanced with the variance ratio dropping to 1-1.2 for firm size, profitability, leverage and other variables. These statistics suggest that the matched sample is better balanced than the raw sample and is well balanced in most, if not all, dimensions.

We present the average treatment effect on the treated (ATET) with Abadie-Imbens (AI) robust standard errors in Panel B of Table 8. We adjust the Mahalanobis estimate for bias from matching on continuous variables using the log of firm size and EBITDA. The estimated ATET for the initial interest rate on the loan is positive with a coefficient of 344 basis points, statistically significant at the 1% level. ATET for loan size is negative and significant at the 5% level, as presented in Column 2. Estimated effect on seniority, security, and financial covenants are also negative with statistically significant coefficients at the 1% level. As expected, ATET for warrants is estimated to be positive (2%) and again statistically significant. These results provide strong evidence that, compared with banks, nonbank lenders charge significantly higher interest rates, are less likely to require collateral or financial covenants but are more likely to include warrants in junior loans to similar borrowers in terms of firm size and profitability.

5 Performance of bank and nonbank borrowers

Our evidence so far shows that compared to banks, nonbank lenders lend to smaller, less profitable, and riskier borrowers. At the same time, nonbank lenders are significantly less likely to include financial covenants in their credit agreements, raising questions as to whether they screen and monitor borrowers to the same extent as banks do, or whether nonbanks simply rely on charging higher interest rates to compensate them for the greater risks involved. To help shed light on these questions, this section explores the ex-post performance of bank and nonbank borrowers as well as the ex-ante announcement returns around loan originations.

5.1 Future performance of nonbank borrowers

We start by asking whether nonbank borrowers are more likely to file for bankruptcy than bank borrowers. If banks are better at monitoring their borrowers, in part through inclusion of financial covenants in their loan agreements, then banks may step in and fix any problems earlier, thereby reducing the probability that their borrowers are forced to file for bankruptcy. We collect bankruptcy dates, as of the end of 2017, from Capital IQ. In our sample, there are 41 deals by 24 borrowers that end in bankruptcy within three years after loan origination. Relative to the number of deals in the data, this corresponds to 4.5% probability of bankruptcy. As a point of reference, over the 1970-2015 period the five-year default rates for BBB and BB rated bonds were 1.5% and 7.0% (Moody's 2016).

Table 9 reports estimates from a linear probability model of bankruptcy over the three years following loan origination. Numbers in parentheses are *t*-statistics corrected for clustering at the firm level. In Column 1, we include only the nonbank dummy, our main explanatory variable of interest. The marginal effect is a 4% increase in the probability of bankruptcy. As we add firm characteristics such as size and EBITDA, the effect of nonbank lender drops to around 3% and is no longer statistically significant. Therefore, the evidence on nonbank borrowers' having a larger likelihood of bankruptcy is rather weak or nonexistent. Controlling for firm characteristics eliminates the difference in bankruptcy rates despite the fact that large interest rate differences remain after controlling for the same characteristics.

Next we study changes in profitability ratios and stock price returns subsequent to loan issuances in our sample. The first two panels of Table 10 present results for year-to-year changes in profitability first for nonbank borrowers and then for various types of borrowers separately, all compared with bank loans as before. The first three columns include all firm-level control variables but firm volatility, sales growth, and market-to-book ratio, which are added in the last three columns.

The coefficient on nonbank-lender dummy is negative and significant only in the first specification, where we study the change in the profitability over the first year after the loan is extended. And this coefficient loses its significance in Column 4, where we include firm volatility, sales growth, market-to-book as controls. Furthermore, analyzing the changes in the second and third years after the loan is made, we find that the coefficient on the nonbank dummy is not statistically different from zero in any specification. Therefore, we conclude that there is only a temporary underperformance potentially connected to the investments made with the loan proceeds.

In Panel B, we include dummies for various nonbank lenders separately in understanding their relation with future borrower profitability. We end up with similar results for FCO and hedge fund/investment manager dummies in the first specification to nonbank lender dummy as in Panel A, with coefficients of 5-6%. Again, we see almost no significance in coefficients for the second and third years. None of the coefficients on other nonbank lender types is significant.

The last two panels repeat similar tests to the ones in the first two panels but use subsequent annualized stock price returns (including delisting returns) as the dependent variable. We skip the first 30 days after loan origination to avoid conflating subsequent returns with announcement returns, which we analyze in Section 5.2. We do not see any significance for nonbank lender dummy or various types of nonbank-lender dummies except for the PE/VC/BDC dummy having a negative and marginally significant coefficient in two of the six specifications..

To summarize, we do not find any evidence that borrowers from nonbank lenders are doing worse than bank borrowers in terms of future profitability. The evidence on bankruptcy probability is rather weak, as well. Taking the coefficient from Column 2 of Table 9, even though it is not significant, a coefficient of 3% implies a 3% higher probability of default for nonbank borrowers. Assuming a salvage value of 50% for defaulted loans, the expected loss for nonbank lenders due to bankruptcies of borrowers over the following three years would be about 0.5% annually. Given that nonbanks charge an interest rate that is about 2% higher than bank rates, nonbank lenders appear to earn high returns even after accounting for loan losses.

5.2 Announcement returns for nonbank borrowers

Our analysis of non-price terms in Table 6 shows that loans from nonbank lenders are significantly less likely to include financial covenants, suggesting that nonbank lenders may engage in less on-going monitoring after loans are originated. Do nonbank lenders engage instead in more ex ante screening of the borrowers they lent to? Nonbank lenders such as hedge funds and other asset managers may have a comparative advantage in identifying good investment opportunities. And the type of unprofitable, R&D intensive firms that these lenders provide funding to may require more ex ante screening than older, more established firms that are already profitable. Lenders to the latter just need to make sure that performance does not deteriorate and that if it does they can step in. If nonbank lenders do engage in more ex ante screening than bank lenders, we may expect nonbank borrowers to experience larger announcement returns around loan origination.

In Table 11 we analyze announcement return around origination of bank versus nonbank loans. Market adjusted cumulative returns are calculated from loan origination through one day after the SEC filing disclosing the terms of the new loan. The sample is limited to loans for which the filing occurs within five calendar days of loan origination and for which the last stock price before origination is at least \$1. Column 1 regresses CARs on the nonbank dummy. The constant term indicates that bank loans experience positive announcement returns of 66 basis points. The coefficient on the nonbank dummy is positive and statistically significant. It indicates that nonbank loans experience announcement returns that are 357 basis points higher than announcement returns for bank loans.

One concern with the univariate results in column 1 is that the coefficient on the nonbank dummy may be driven by returns experienced by unprofitable firms that are able to secure debt financing. In column 2, we control for negative EBITDA as well as firm size. Neither coefficient is statistically significant, and their inclusion does not affect the coefficient on the nonbank dummy. In column 3, we control for additional firm characteristics such as market-to-book, leverage, firm age, and profitability. The coefficient on the nonbank dummy is reduced from 341 to 293 basis points, but it retains statistical significance, while none of the controls are statistically significant.

Our results that nonbank loans experience larger announcement returns than bank loans differ from James (1987) who finds that during the 1974-1983 period bank loans experience positive announcement returns while private placements are if anything associated with negative returns. Billett, Flannery, and Garfinkel (1995) on the other hand find average returns for private placements that are actually larger than returns for bank loans but that are not statistically significant, perhaps due to the small number of private placements in the data. The composition of our nonbank loan sample is very different from James (1987). In the sample used by James (1987), about 70% of private placements involve insurance companies. Our sample of nonbank loans has relatively few insurance companies and is instead dominated by finance companies, hedge funds, private equity, and venture capital firms. In our data, insurance companies lend to firms with more PPE and are as likely as banks to include financial covenants in their loans. Thus, it may be that because they rely on the value of the real estate collateral backing their loans and on financial covenants to catch deterioration in borrower's financial conditions, insurance do not engage in as much ex-ante screening as other nonbank lenders. In fact, in unreported results, we find that loans from insurance companies are associated with 144 basis points lower announcement returns than loans from other nonbanks, though given the small number of insurance companies in the data, the difference is not statistically significant.

Overall, the fact that nonbank loans experience more positive announcement returns than bank loans is potentially consistent with nonbank lenders relying more on screening rather than ex post monitoring of borrower's performance.

6 Local banking conditions

Lastly, we study characteristics of the local banking markets in which borrowing firms operate. Table 12 reports the results of linear probability model of the propensity to borrow from a nonbank lender on the characteristics of the county in which borrower's headquarters are located. In column 1 we regress the probability of borrowing from a nonbank lender on the capitalization of banks operating in the firm's county and on the concentration of deposits as a proxy for bank competition. To make sure that the results are not driven by time series trends in bank capitalization and in the propensity to borrow from nonbanks, we include year fixed effects. Identification is therefore based on within-year variation across counties in the capitalization of local banks and in the propensity of local firms to borrow from nonbanks. The coefficient on the bank leverage ratio is negative and statistically significant indicating that when local banks are better capitalized, so that their ratio of tier 1 capital to total assets is larger, firms are less likely to turn to nonbank lenders. This effect is economically meaningful. An increase of 1% in the tier 1 leverage ratio of local banks is associated with 5.1 percentage points decline in the propensity to borrow from a nonbank lender. Relative to the 30% unconditional probability of borrowing from a nonbank lender, this finding represents a 17% decline.

The coefficient on deposit concentration, which following the existing literature (Petersen and Rajan 1995) we use as a proxy for local bank competition, is negative and statistically significant, suggesting that firms located in more competitive banking markets are actually more likely to turn to nonbanks for loan financing. This result is consistent with the predictions of the theoretical model of Donaldson, Piacentino, and Thakor (2017). In their model, firms choose whether to invest in more versus less innovative projects, with the latter having higher expected payoffs but also requiring more monitoring by lenders. Bank competition destroys the incentive of banks to monitor innovative firms, causing such firms to opt for less innovative projects. Nonbank lender's high cost of capital, on the other hand, acts as a commitment device to fund only innovative projects and to monitor. In equilibrium bank and nonbank lenders coexist, with nonbanks lending to more innovative firms. Consistent with the model of Donaldson, Piacentino, and Thakor (2017), when we examine in Tables 2-4 the characteristics of firms that borrow from nonbank lenders, we will see that nonbank borrowers spend much more on R&D than bank borrowers. The magnitude of the effect of bank competition is economically meaningful – an increase in deposit concentration of 0.10 is associated with 3.3 percentage points decline in the propensity to borrow from a nonbank lender.

Column 2 of Table 12 controls for industry instead of year fixed effects, while column 3 controls for both industry and year fixed effects.[14] We include industry fixed effects to make sure that the results are not driven by variation across industries in the propensity to borrow from banks (due to, for example, differences in the composition of assets that can be used as collateral) and spatial concentration of industries in certain geographies. For example, it could be that high-tech firms that have few tangible assets are located primarily in wealthier counties that also happen to be more competitive banking markets in which banks have low capitalization ratios due to the presence of many lending opportunities. Controlling for industry fixed effects generates similar results indicating that variation across industries is not driving our results.

Since we do not have exogenous variation in the capitalization of local banks, to further address the concern that bank capitalization and concentration could be picking up the effect of shocks to local demand for credit, columns 4-8 control for additional measures of local economic conditions: banking deposits, per capita personal income, growth in per capita personal income, and unemployment rate. While we cannot rule out that counties with less well capitalized banks or more concentrated banking markets are different on unobservable characteristics, it is comforting that none of the observable measures of local economic performance are statistically significant and that controlling for them does not have much effect on the coefficients of interest.

Overall, the results of Table 12 point to county-level drivers of the propensity to borrow from nonbank lenders: capitalization of local banks and competition among them. The first result is consistent with less well capitalized banks being less willing to extend C&I loans to middle market firms. The second result is consistent with bank competition differentially affecting the

[14] Industry fixed effects are based on Fama-French 17 industries. Results are similar with Fama-French 12 and 48 industries.

ability and willingness of bank and nonbank lenders to screen and monitor innovative firms (Donaldson, Piacentino, and Thakor 2017).

7 Conclusion

We present novel systematic evidence on direct lending by nonbank financial intermediaries to publicly traded middle market firms during the post crisis period. Such lending is widespread with about one third of all loans in our data being extended by nonbanks. Firms located in counties with less well capitalized banks and in less concentrated banking markets are more likely to turn to nonbank lenders for debt financing. Smaller, unprofitable, R&D-intensive firms are significantly more likely to borrow from nonbanks. Consistent with market segmentation and with banks having lower cost of debt, nonbank loans carry significantly higher interest rates. Controlling for firm characteristics and other loan terms, the average difference in interest rates is about 200 basis points. This difference is even larger at the zero EBITDA boundary, where using fuzzy RDD we estimate the causal effect of nonbank lending to be around 480 basis points.

Consistent with lenders trying to match the interest rate exposure of their assets and liabilities (and with there being frictions in hedging such exposure), we find that nonbank loans are significantly more likely to carry fixed interest rates compared to bank loans. Nonbank lenders are significantly less likely than banks to include financial covenants or performance pricing provisions in their loans. Nevertheless, following loan origination, firms that borrow from nonbanks appear to perform as well as firms that borrow from banks. Thus rather than relying on financial covenants to monitor borrowers' ex-post performance, nonbank lenders appear to engage in extensive ex-ante screening. Consistent with this idea we find large positive abnormal returns around announcements of nonbank loans.

Appendix A. Details on sample construction

We start sample construction by randomly sampling a set of 750 firms from the domestic population of publicly traded Compustat firms during the period of 2010-2015 with revenues between $10 million and $1 billion. We require that the firms have book leverage of at least 5% and exclude financial firms and utilities. We also exclude ADRs and firms that are incorporated or have their headquarters outside the US. A small number of firms move from abroad to the US or vice versa during the sample period. We include such firms only for the period during which both the location of their headquarters as well as their incorporation are in the US.

Next, we use Capital IQ to obtain a list of each firm's debt agreements during the period from 2010-2015 along with a link to the SEC filing in EDGAR. We include credit agreements, debt & loan agreements, notes agreements and securities purchase agreements. We exclude bonds and supplemental filings such as guarantee agreements, loan modifications, covenant waivers, etc.

To avoid having to manually exclude a large number of bonds, we limit our download of credit documents to instruments for debt amounts of less than $250 million. We obtain syndicated loans in excess of $250 million from DealScan. as described further below.

Loan amendments are not necessarily filed as exhibits, but might simply be described in a short paragraph in a company's 10-Q or 10-K filing and are thus much more difficult to track consistently than contracts that are stated in full. Since this paper focuses on sources of funds and initial contract terms rather than renegotiations, we drop all simple amendments and retain only original debt contracts as well as amended and restated debt contracts, which presumably represent more substantial changes. We also exclude promissory notes that are issued pursuant to an existing credit agreement, such as notes evidencing a drawdown of a line of credit. Finally, we drop eight debtor-in-possession credit agreements.

We obtain the identity of the borrower, the lead lender, as well as the origination date for the remaining contracts and match them to DealScan based on these three data items. Because firms sometimes borrow through their subsidiaries, we obtain a list of subsidiaries for our sample firms from Exhibit 21 of their 10-K filings and cross-reference these entities with DealScan as well. Where possible, we obtain data on loan characteristics for the matched loans from DealScan. Importantly, we do not include in our sample contracts from DealScan that do not have a match in our data extract from Capital IQ/EDGAR. Manually searching for 25 of these observations in Capital IQ and EDGAR, we verify that the majority of these DealScan observations are in fact amendments rather than originations. The remaining observations involve either relatively small loans issued by subsidiaries of our sample firms that were not filed with the SEC by the sample firm presumably due to lack of materiality, or loans issued after a company has ceased to file with the SEC. We conclude that coverage of debt contracts in Capital IQ appears reliable during the sample period.

Since we exclude instruments larger than $250 million from the Capital IQ search, we obtain a list of all deals in excess of $250 million from DealScan. Because DealScan contains a large number of amendments, we search Capital IQ for any debt contracts originated at the same time as the DealScan contract and exclude DealScan observations that correspond to amendments in Capital IQ or that cannot be found in Capital IQ (e.g. because they are amendments that are not filed in an exhibit or because the firm is no longer public). Among the DealScan observations that can be matched to Capital IQ, 43% are amendments.

We manually code debt contracts that could not be matched to DealScan. Each loan is assigned a lender type based on the identity of the lender or, in the case of multi-lender loans, the lead lender. The lead lender is assumed to be first lender mentioned in the header of the contract. If lender roles are assigned, we take the first lender that is either named as administrative agent, lead arranger, or agent. For observations taken from DealScan, we identify as the lead arranger the institution that is given lead arranger credit in DealScan or has one of the lender roles designated above. There are a few cases in which an administrative agent has a purely administrative role without actually lending to the borrower. For example, some hedge funds rely on an investment bank to administer a deal. In cases in which the first mentioned lender is an administrative agent, we verify that this institution also acts as a lender. If it does not, then we record the identity of the first institution that is listed as a lender on the signature page or commitment schedule.

Lenders are classified into the following types: bank, bank-affiliated finance company, finance company, investment bank, private equity/venture capital, hedge fund, insurance company, investment manager, business development company, other collective investments (such as collateralized loan obligations or mutual funds), government, individual, and nonfinancial corporations. We first cross-references lenders against lists of business development companies (from Capital IQ), hedge funds (from SEC form ADV), and private equity funds (from Preqin). If a lender is not on one of these lists, we use the business description in Capital IQ. Contracts obtained from government entities (such as the Export-Import Bank), individuals, and “other” lenders are excluded from the analysis. Contracts entered into with nonfinancial corporations are typically related to a business transaction, primarily seller financing, or are loans between affiliated firms.

Appendix B. Variable definitions

Variable	Definition	Source
Loan characteristics		
Annual fee	Fee the borrower has to pay to lender annually, expressed in basis points of the entire commitment. Not to be confused with a commitment fee, which is charged only on the unused portion of a credit line	Manual collection, DealScan
Convertible	Indicator equals one if the debt is convertible, zero otherwise	Manual collection
Financial covenants	Indicator equals one if the debt contract contains any financial covenants, zero otherwise	Manual collection, DealScan
Fixed rate loan	Indicator equals one if debt is fixed rate, zero if debt is floating rate	Manual collection, DealScan
Initial interest rate	Equals fixed rate for fixed rate debt, level of 1-month US Dollar LIBOR (adjusted for interest rate floors) at origination plus spread for floating rate debt	LIBOR levels obtained from Federal Reserve Bank of St. Louis FRED database
Loan size	Total size of the commitment	Manual collection, DealScan
Ln(amount)	Natural log of loan size	Manual collection, DealScan
Maturity	Maturity of the debt expressed in years	Manual collection, DealScan
Nonbank	Indicator equals one if the lender is a nonbank, zero if it is a bank	Capital IQ, Preqin, SEC form ADV
Performance pricing	Indicator equals one if debt has a performance pricing provision, zero otherwise	Manual collection, DealScan
Second lien	Indicator equals one if the loan is second lien, zero if it is first lien or unsecured	Manual collection, DealScan
Security	Indicator equals one if the debt is secured by collateral, zero otherwise	Manual collection, DealScan

Seniority	Indicator equals one if the debt is senior, zero otherwise	Manual collection, DealScan
Upfront fee	Fee the borrower has to pay to lender at origination, expressed in basis points of the entire commitment	Manual collection, DealScan
Warrants	Indicator equals one if the lender receives warrants in conjunction with the debt issue, zero otherwise	Manual collection, DealScan
Firm characteristics		
Cash	Cash and cash equivalents divided by total assets.	Capital IQ
Current ratio	Current assets divided by current liabilities.	Capital IQ
Coverage ratio	EBITDA divided by interest expense.	Capital IQ
EBITDA	Earnings before interest, taxes, depreciation and amortization (EBITDA).	Capital IQ
EBITDA < 0	Indicator equals one if EBITDA is negative, zero otherwise.	Capital IQ
Firm age	Number of years elapsed since the firm was founded.	Capital IQ, EDGAR 10-K filings
Inventory	Inventory divided by total assets.	Capital IQ
Leverage	Long-term debt plus debt in current liabilities divided by total assets.	Capital IQ
Market-to-book	Common shares outstanding times stock price plus preferred stock plus long-term debt plus debt in current liabilities, divided by total assets	Capital IQ
Profitability	Ratio of EBITDA to total assets.	Capital IQ
Δ Profitability	Annual change in the ratio of EBITDA to total assets.	Capital IQ
Receivables	Receivables divided by total assets.	Capital IQ
Research expense	Research expense divided by sales.	Capital IQ

Sales growth	Sales in year *t* divided by sales in year *t*-1 minus one	Capital IQ
PP&E	Net property, plant and equipment divided by total assets.	Capital IQ
Total Assets	Total book assets.	Capital IQ
Volatility	Standard deviation of daily stock returns measured over 365 calendar days ending 120 days prior to loan origination, multiplied by the square root of 252. At least 120 daily returns must be available.	CRSP
County characteristics		
Bank leverage ratio	Deposit-weighted average of the tier 1 leverage ratio of bank holding companies with branches in the county of the firm's headquarters.	Summary of Deposits, Y9-C
Deposit concentration	Herfindahl-Hirschman Index of bank deposit concentration in the county of the firm's headquarters. Deposit shares within a county are aggregated across multiple banks owned by the same bank holding company. Deposits are reported as of June of the year prior to loan origination.	Summary of Deposits
Ln(Total deposits)	Natural logarithm of the aggregate value of deposits in the county of the firm's headquarters.	Summary of Deposits
Ln(Personal income)	Natural logarithm of the per capita personal income in the county of the firm's headquarters.	BEA Regional Economic Accounts
Unemployment rate	Unemployment rate in the county of the firm's headquarters.	BLS Local Area Unemployment Statistics

The following variables are winsorized at the 1st and 99th percentile: leverage, current ratio, coverage ratio, PP&E, cash, receivables, inventory, market-to-book, research expense, sales growth, and volatility. In addition, the leverage, sales growth, research expense, profitability, and Δ profitability measures are capped at a maximum value of one and the minimum value for profitability and Δ profitability is set to minus one to eliminate outliers that persist after winsorization.

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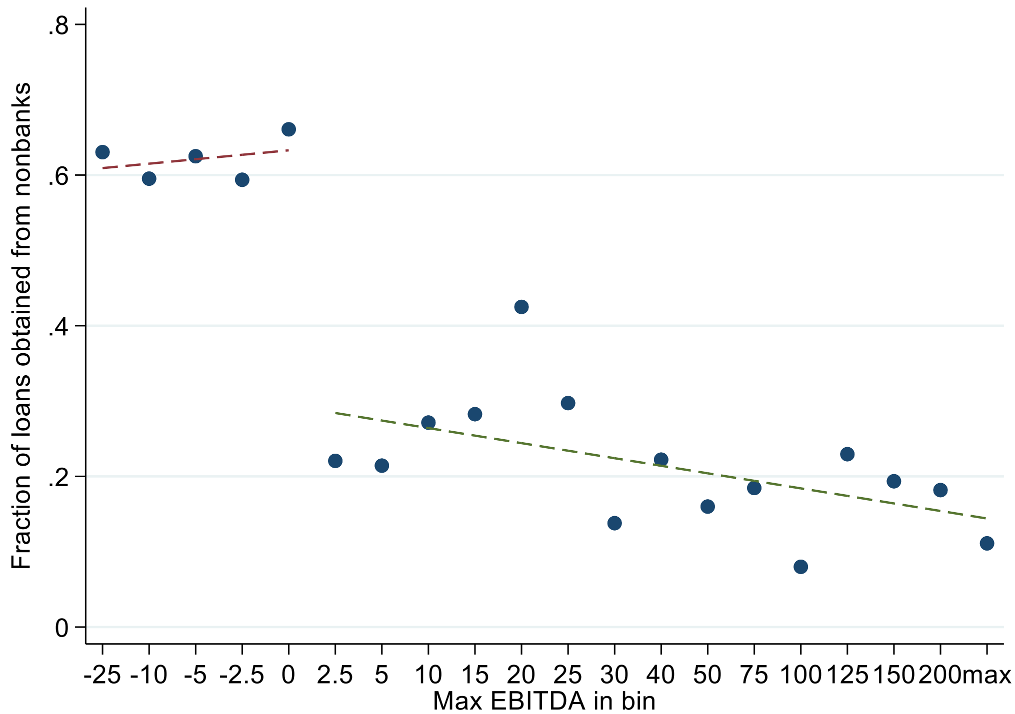

Figure 1: Fraction of loans obtained from nonbanks by EBITDA bin

This figure shows what fraction of loans is obtained from nonbanks at different levels of EBITDA. Loans are allocated into twenty bins based on the borrower's EBITDA at the end of the fiscal year prior to loan origination. The x-axis shows the upper limit of EBITDA for each bin. The choice of bin limits roughly follows the distribution obtained by splitting EBITDA into twenty quantiles, rounded to symmetric numbers.

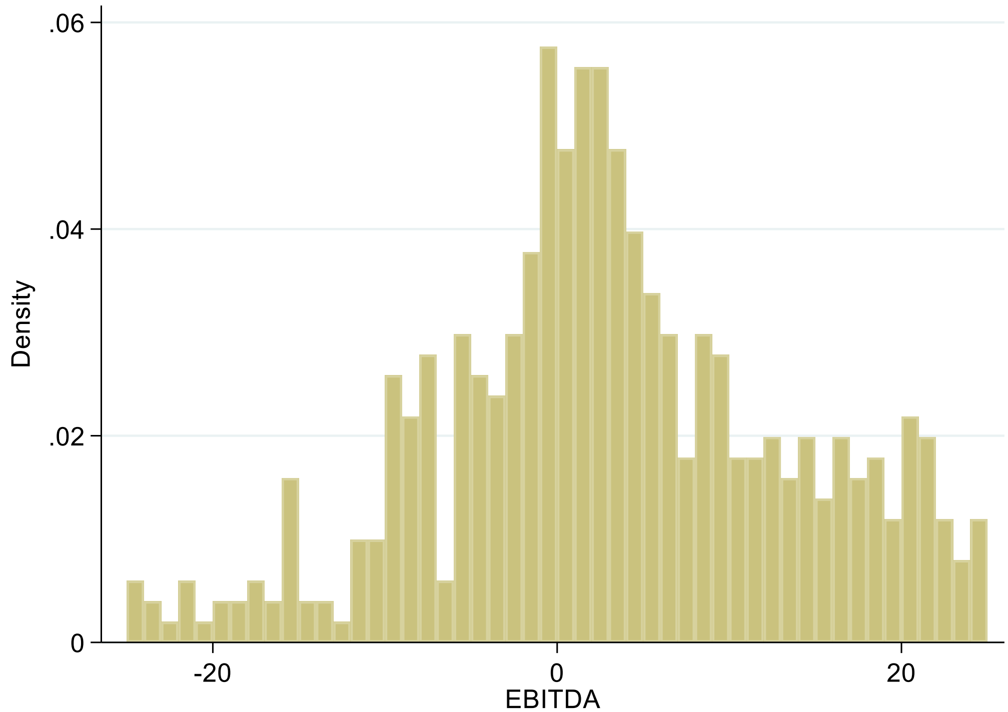

Figure 2: Histogram of trailing twelve month EBITDA

This figure shows a histogram of trailing twelve month EBITDA for those borrowers whose EBITDA is within the range of minus 25 million dollars to plus 25 million dollars. Bin width is one million dollars. The sample includes all borrowings of a random sample of 632 middle-market firms originated and filed with the SEC during the 2010-2015 period.

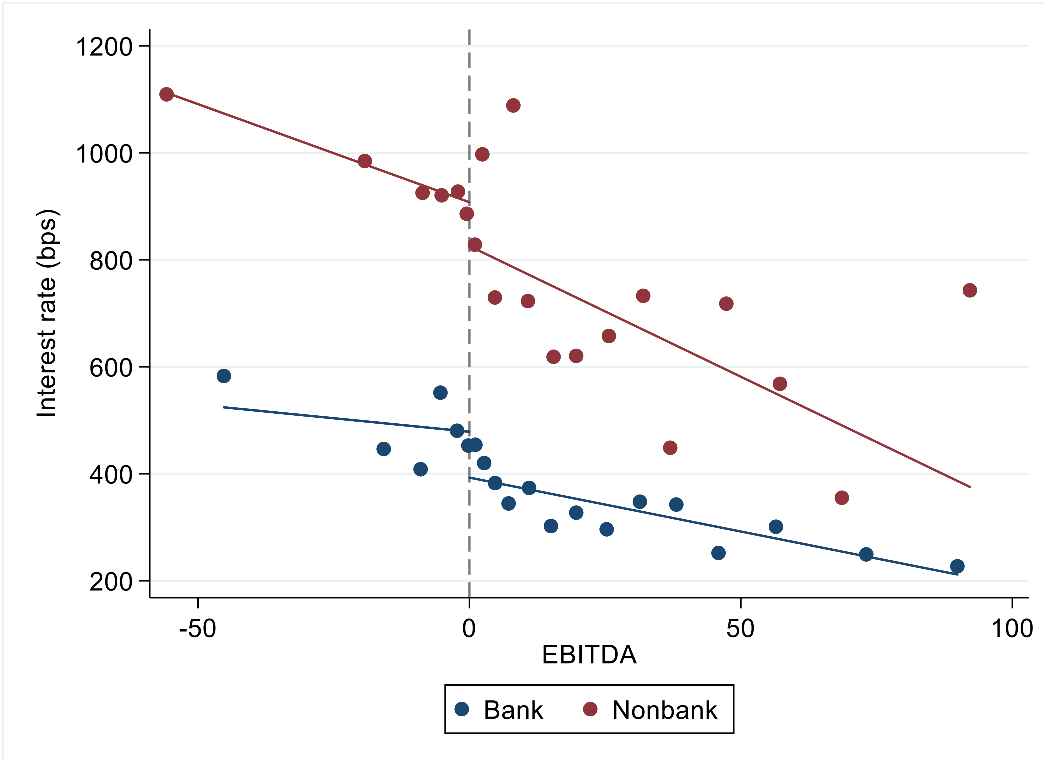

Figure 3: Relation between interest rate and EBITDA
This figure shows the interest rate paid by nonbank and bank borrowers, respectively, at different levels of EBITDA. Nonbank and bank loans each are allocated into twenty quantiles based on the borrower's EBITDA over the trailing twelve-month period. The figure includes the loans of sample borrowers with an EBITDA between minus $100 million and plus $100 million.

Table 1: Number of loans originated, lender types and DealScan match rates

Panel A reports for each year the total number of loans originated and the share extended by nonbanks. Panel B reports for each nonbank lender type, the number loans originated and the percentage included in the DealScan database. The sample includes all borrowings of a random sample of 632 middle-market firms originated and filed with the SEC during the 2010-2015 period. Multiple tranches within a given package are treated as a single observation.

Panel A: Loans originated per year

	Obs.	% nonbank
2010	189	31.22
2011	216	28.24
2012	199	32.66
2013	164	31.70
2014	170	29.41
2015	97	35.05
Total observations	1,035	31.01

Panel B: Nonbank lender types and DealScan match rates

	Obs.	% of nonbank deals	% tracked in DealScan
Bank FCO	31	9.66	29.03
FCO	84	26.17	22.62
Investment bank	36	11.21	77.78
Insurance	14	4.36	7.14
BDC	11	3.43	9.09
PE/VC	60	18.69	0.00
Hedge fund	56	17.45	7.14
Investment manager	24	7.48	8.33
Other	5	1.56	20.00
Total observations	321	100.00	20.25

Table 2: Summary statistics for bank vs. nonbank loans

This table reports firm and loan characteristics for bank and nonbank loans. The sample includes all non-bond borrowings of a random sample of 632 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level using the average value of each variable across the tranches in a deal. Variable definitions are in Appendix B. t-tests for differences in means allow for unequal variances across groups. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Nonbank loans		Bank loans		Difference
	Obs.	Mean (St. dev.)	Obs.	Mean (St. dev.)	in means (t-statistic)
Total assets	304	324.45	697	595.72	-271.28***
		(652.05)		(1030.40)	(-5.02)
EBITDA	309	20.52	696	72.10	-51.58***
		(65.05)		(146.21)	(-7.74)
Profitability	303	-0.11	694	0.09	-0.19***
		(0.32)		(0.17)	(-9.92)
Leverage	304	0.38	697	0.26	0.12***
		(0.30)		(0.23)	(6.08)
Market-to-book	281	1.70	649	1.58	0.11
		(1.50)		(1.17)	(1.14)
Research expense	304	0.09	697	0.04	0.04***
		(0.17)		(0.10)	(4.03)
PP&E	302	0.24	690	0.27	-0.02
		(0.25)		(0.26)	(-1.34)
Cash	304	0.12	697	0.12	0.01
		(0.15)		(0.13)	(0.69)
Receivables	304	0.16	697	0.15	0.01
		(0.14)		(0.12)	(0.97)
Inventory	304	0.13	697	0.14	-0.01
		(0.16)		(0.17)	(-0.73)
Firm age	321	28.59	714	37.98	-9.39***
		(27.80)		(32.99)	(-4.74)
Sales growth	289	0.13	669	0.13	0.00
		(0.39)		(0.29)	(0.10)
Volatility	217	0.71	595	0.54	0.17***
		(0.36)		(0.27)	(6.24)
Deal size	321	72.53	713	184.86	-112.33***
		(190.14)		(330.56)	(-6.89)
Maturity	319	3.91	704	3.99	-0.08
		(2.43)		(2.06)	(-0.53)
Fixed rate loan	314	0.55	697	0.04	0.51***
		(0.49)		(0.19)	(17.79)
Initial interest rate (bps)	308	822.82	660	333.01	489.81***
		(392.78)		(175.78)	(20.93)
Senior	321	0.69	712	0.98	-0.29***
		(0.47)		(0.15)	(-10.94)
Second lien	321	0.05	714	0.00	0.04***
		(0.21)		(0.07)	(3.67)
Secured	321	0.82	696	0.85	-0.03
		(0.39)		(0.36)	(-1.31)
Performance pricing	321	0.06	714	0.34	-0.29***
		(0.22)		(0.47)	(-13.45)

	Nonbank loans		Bank loans		Difference
	Obs.	Mean (St. dev.)	Obs.	Mean (St. dev.)	in means (t-statistic)
Upfront fee (bps)	255	43.30 (90.54)	627	17.56 (41.55)	25.74*** (4.36)
Annual fee (bps)	254	3.57 (27.75)	632	1.83 (9.11)	1.74 (0.98)
Financial covenants	321	0.50 (0.50)	714	0.86 (0.35)	-0.36*** (-11.72)
Warrants	321	0.24 (0.43)	712	0.02 (0.13)	0.23*** (9.25)
Convertible	321	0.14 (0.35)	712	0.00 (0.05)	0.14*** (7.14)

Table 3: Probability of borrowing from a nonbank lender

This table reports results from a linear probability model of whether a loan is extended by a nonbank lender. The sample includes all non-bond borrowings of a random sample of 632 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level using the average value of each variable across the tranches in a deal. Industry fixed effects are based on Fama-French 12 industries. *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)
Ln(Assets)	-0.03**	0.00	-0.01	-0.03
	(-1.97)	(0.20)	(-0.38)	(-0.45)
EBITDA	-0.0004**	-0.0004**	-0.0004**	-0.0001
	(-2.22)	(-2.43)	(-2.44)	(-0.53)
EBITDA < 0		0.33***	0.36***	0.24**
		(7.15)	(7.84)	(2.27)
Leverage	0.43***	0.41***	0.46***	0.31*
	(5.65)	(5.43)	(6.15)	(1.82)
Market-to-book	-0.02	-0.01	-0.02	-0.06*
	(-1.39)	(-1.13)	(-1.42)	(-1.83)
Research expense	0.49***	0.16	0.12	-0.25
	(2.91)	(0.94)	(0.71)	(-0.39)
PP&E	-0.04	0.02	-0.02	-0.10
	(-0.44)	(0.23)	(-0.20)	(-0.23)
Current ratio	-0.01	-0.01		
	(-1.34)	(-1.33)		
Cash			-0.02	0.04
			(-0.15)	(0.10)
Receivables			0.09	0.18
			(0.53)	(0.30)
Inventory			-0.36***	0.62
			(-3.13)	(0.93)
Ln(Firm age)	-0.06***	-0.03	-0.01	-0.39
	(-2.72)	(-1.54)	(-0.75)	(-1.37)
Constant	0.51***	0.19*	0.18	1.70
	(4.26)	(1.84)	(1.44)	(1.22)
Year effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	No
Borrower effects	No	No	No	Yes
Observations	920	920	920	920

Table 4: Multinomial logit regression for borrowing from a specific type of nonbank lender

This table reports relative risk ratios from multinomial logit regressions predicting lender type. The sample includes all borrowings of a random sample of 632 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level using the average value of each variable across the tranches in a deal. Bank loans are the base outcome in all three models. Model 1 aggregates nonbank lenders into four groups: 1) finance companies (FCOs) and bank-affiliated FCOs; 2) investment banks; 3) business development companies (BDC), private equity funds (PE), venture capital funds (VC), hedge funds (HF), and investment managers (IM), collectively referred to as asset managers; and 4) insurance companies. Model 2 further splits bank-affiliated FCOs and unaffiliated FCOs into separate groups. The full model is estimated, but only the results for FCOs are tabulated. Model 3 allows for five nonbank groups: 1) FCO or bank-affiliated FCO; 2) investment bank; 3) BDC, PE, or VC; 4) HF or IM; and 5) insurance companies. The full model is estimated, but only the results for BDCs, PEs, and VCs as well as HFs and IMs are tabulated. Industry fixed effects are based on Fama-French 12 industries. z-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Model 1				Model 2		Model 3	
	FCO / Bank FCO	Investment bank	Asset managers	Insurance	Bank FCO	Unaffiliated FCO	BDC / PE / VC	Hedge fund / IM
Ln(Assets)	1.09	2.40***	0.81*	1.48	1.05	1.09	0.75*	0.84
	(0.74)	(2.86)	(-1.53)	(0.77)	(0.20)	(0.64)	(-1.68)	(-1.06)
EBITDA	0.99***	1.00*	0.99*	1.00	0.9906**	0.9921**	0.9894	0.9904
	(-2.99)	(-1.74)	(-2.03)	(-0.99)	(-2.23)	(-2.45)	(-1.49)	(-1.56)
EBITDA < 0	3.20***	5.79***	7.54***	12.88***	1.93	3.91***	6.96***	9.06***
	(3.23)	(2.81)	(5.96)	(3.13)	(1.07)	(3.32)	(4.04)	(5.60)
Leverage	9.46***	13.33***	22.10***	0.26	13.79***	8.17***	10.38***	43.65***
	(3.91)	(2.89)	(5.19)	(-0.47)	(3.23)	(3.26)	(2.90)	(6.08)
Sales growth	0.69	1.01	2.34**	1.30	0.88	0.65	5.59***	1.51
	(-0.99)	(0.02)	(2.08)	(0.19)	(-0.22)	(-0.96)	(3.64)	(0.90)
Research expense	0.79	0.01	3.45	0.00*	0.02	1.43	13.75**	0.73
	(-0.16)	(-1.18)	(1.07)	(-1.74)	(-1.12)	(0.21)	(2.20)	(-0.21)
PP&E	0.38	0.62	1.07	98.11**	1.09	0.25	1.05	1.15
	(-1.11)	(-0.47)	(0.08)	(2.31)	(0.06)	(-1.53)	(0.05)	(0.12)
Cash	0.78	5.31	0.11*	0.04	0.10	1.31	0.37	0.01**
	(-0.20)	(1.03)	(-1.69)	(-0.95)	(-1.01)	(0.20)	(-0.72)	(-2.27)
Receivables	1.21	2.33	2.64	0.05	9.50	0.56	4.70	1.29
	(0.13)	(0.36)	(0.71)	(-0.77)	(0.80)	(-0.39)	(0.96)	(0.14)
Inventory	0.08***	0.05*	0.15	1.07	0.07*	0.08***	0.05*	0.24
	(-2.97)	(-1.89)	(-1.60)	(0.05)	(-1.72)	(-2.98)	(-1.94)	(-1.07)

Ln(Firm age)	1.09	0.96	0.93	1.59*	1.00	1.16	1.18	0.83
	(0.50)	(-0.20)	(-0.39)	(1.81)	(0.01)	(0.79)	(0.58)	(-0.97)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-zero obs. in category	102	35	129	13	31	71	53	76
Total observations	940	940	940	940	940	940	940	940

Table 5: Initial interest rate charged on bank versus nonbank loans

This table reports the results from regressions of the initial interest rate charged on a loan on lender type indicators, loan and firm characteristics. Initial interest rate is equal to the fixed rate for fixed rate loans and to 3-month LIBOR plus spread for floating rate loans. The sample includes all borrowings of a random sample of 632 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level using the average value of each variable across the tranches in a deal. Variable definitions are in Appendix B. Industry fixed effects are based on Fama-French 12 industries. *t*-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nonbank	481.01***	365.38***	222.78***	218.55***	186.81***			292.19***
	(12.93)	(12.95)	(7.50)	(5.90)	(6.66)			(5.47)
Bank FCO						-30.24	-23.25	
						(-1.24)	(-0.82)	
FCO						244.40***	193.96***	
						(5.66)	(4.74)	
Investment Bank						218.07***	168.42***	
						(4.80)	(3.73)	
PE/VC/BDC						416.16***	399.06***	
						(10.04)	(6.74)	
Hedge fund/IM						435.83***	412.89***	
						(7.66)	(7.76)	
Insurance						12.71	2.24	
						(0.25)	(0.05)	
Ln(Amount)			-6.42	-11.92	9.39	-9.32	3.07	-6.92
			(-0.77)	(-1.25)	(1.11)	(-1.27)	(0.39)	(-0.37)
Performance pricing			-58.90***	-37.35***	-39.73***	-56.99***	-40.47***	-30.78
			(-4.40)	(-2.60)	(-3.07)	(-4.74)	(-3.45)	(-1.03)
Upfront fee				0.72***				
				(3.01)				
Annual fee				0.91***				
				(2.84)				
Warrants			96.03**	101.29**	51.55	60.17*	13.70	11.45
			(2.44)	(2.21)	(1.19)	(1.66)	(0.36)	(0.11)
Convertible debt			-177.47***	-184.00***	-134.90*	-240.71***	-158.09**	-152.20
			(-3.11)	(-3.41)	(-1.76)	(-3.91)	(-1.98)	(-1.37)
Financial covenants			1.89	-15.16	-6.73	21.83	13.99	38.89
			(0.08)	(-0.59)	(-0.25)	(0.96)	(0.56)	(0.76)
Security			53.06**	43.00*	20.89	68.89***	40.07**	31.94
			(2.35)	(1.94)	(1.06)	(3.32)	(2.46)	(0.59)

Second lien			413.58***	382.24***	435.06***	390.24***	424.07***	373.88***
			(5.66)	(4.30)	(6.05)	(5.55)	(5.37)	(3.22)
Maturity			-9.98*	-9.78*	-3.87	-4.67	1.15	1.91
			(-1.93)	(-1.90)	(-0.83)	(-0.98)	(0.25)	(0.22)
Fixed rate loan			217.72***	200.92***	180.48***	166.55***	132.05***	152.32**
			(6.35)	(5.29)	(4.84)	(5.29)	(3.83)	(2.41)
Seniority			-83.12**	-85.68**	-110.10***	-51.78	-60.36	7.09
			(-2.27)	(-2.04)	(-2.88)	(-1.55)	(-1.63)	(0.10)
Ln(Assets)		-48.64***	-22.50**	-16.06	-37.75***	-22.78**	-34.72***	27.86
		(-6.65)	(-2.30)	(-1.47)	(-3.52)	(-2.55)	(-3.56)	(0.70)
Profitability		-225.98***	-197.29***	-168.91***	-272.48***	-187.94***	-225.50***	-309.91**
		(-3.22)	(-3.12)	(-2.72)	(-4.38)	(-3.17)	(-3.57)	(-2.44)
Leverage		155.57***	138.15***	146.17***	157.66***	135.76***	160.72***	88.29
		(3.44)	(4.05)	(4.13)	(3.57)	(4.07)	(3.77)	(0.99)
Research		-17.55	-72.33	-26.95	26.65	-143.44*	-18.13	39.95
expense		(-0.17)	(-0.84)	(-0.31)	(0.24)	(-1.75)	(-0.17)	(0.10)
PP&E		-63.28	-60.29	-82.38	-69.67	-56.39	-64.60*	269.10
		(-1.02)	(-1.19)	(-1.59)	(-1.64)	(-1.30)	(-1.85)	(1.31)
Cash		-57.83	-59.67	-68.36	-108.13	-37.39	-76.23	77.52
		(-0.67)	(-0.78)	(-0.88)	(-1.56)	(-0.54)	(-1.17)	(0.33)
Receivables		-214.29**	-143.88	-164.17*	-122.18	-181.46**	-139.02*	-95.93
		(-2.09)	(-1.61)	(-1.74)	(-1.38)	(-2.17)	(-1.84)	(-0.34)
Inventory		-39.32	-65.18	-120.21*	-31.84	-56.19	-10.73	401.95
		(-0.52)	(-1.00)	(-1.77)	(-0.54)	(-0.97)	(-0.21)	(1.23)
Ln(Firm age)		-14.03	-16.04	-16.77	-19.48*	-10.47	-14.19	106.66
		(-1.10)	(-1.54)	(-1.56)	(-1.71)	(-1.17)	(-1.49)	(0.70)
Volatility					147.21***		102.86***	
					(3.66)		(2.94)	
Growth					25.81		11.34	
					(0.72)		(0.33)	
Market-to-book					-12.09		-12.57*	
					(-1.62)		(-1.67)	
Constant	400.60***	737.52***	696.70***	687.19***	680.17***	631.01***	597.46***	-586.03
	(12.25)	(8.91)	(8.21)	(8.16)	(7.26)	(8.32)	(6.83)	(-0.85)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Firm effects	No	No	No	No	No	No	No	Yes
Observations	968	921	902	771	711	897	706	902

Table 6: Non-price terms of bank versus nonbank loans

This table reports the results from OLS regressions of non-price loan terms on lender type indicators, loan and firm characteristics. The sample includes all borrowings of a random sample of 632 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level using the average value of each variable across the tranches in a deal. Variable definitions are in Appendix B. Industry fixed effects are based on Fama-French 12 industries. *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

Panel A: Basic non-price terms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(Amount)	Ln(Amount)	Maturity	Maturity	Seniority	Seniority	Security	Security
Bank FCO	-0.84***	-0.57**	-0.21	-0.08	-0.20**	-0.18**	0.08*	0.07
	(-2.64)	(-2.13)	(-0.49)	(-0.20)	(-2.44)	(-2.22)	(1.70)	(1.54)
FCO	-0.79***	-0.40***	-0.21	0.05	-0.15***	-0.16***	0.08**	0.04
	(-4.08)	(-3.09)	(-0.74)	(0.19)	(-3.22)	(-3.03)	(2.49)	(1.14)
Investment bank	0.93***	-0.02	0.77***	0.41*	-0.18**	-0.21**	0.05	0.05
	(3.10)	(-0.16)	(2.67)	(1.74)	(-2.19)	(-2.56)	(0.85)	(0.90)
PE/VC/BDC	-1.82***	-0.60***	-0.54*	0.32	-0.50***	-0.48***	-0.02	-0.09
	(-7.27)	(-3.05)	(-1.80)	(0.99)	(-6.53)	(-5.86)	(-0.34)	(-1.60)
Hedge fund/IM	-1.73***	-0.58***	-0.88***	-0.06	-0.35***	-0.31***	-0.20**	-0.24***
	(-6.22)	(-2.74)	(-2.67)	(-0.25)	(-3.39)	(-3.62)	(-2.22)	(-3.31)
Insurance	-0.55**	-0.22	5.11***	4.99***	-0.20*	-0.19*	-0.07	-0.06
	(-2.10)	(-0.42)	(4.26)	(5.28)	(-1.72)	(-1.80)	(-0.62)	(-0.52)
Ln(Assets)		0.87***		0.28***		0.02**		-0.03**
		(22.73)		(3.34)		(2.31)		(-2.15)
Profitability		-0.02		1.09**		-0.03		0.03
		(-0.09)		(2.39)		(-0.36)		(0.40)
Leverage		0.56***		-0.08		-0.10		0.04
		(3.49)		(-0.25)		(-1.60)		(0.72)
Research expense		0.52		0.43		0.07		0.33**
		(1.10)		(0.63)		(0.50)		(2.54)
Tangibility		-0.19		0.78*		-0.01		-0.09
		(-0.79)		(1.91)		(-0.20)		(-1.17)
Cash		0.46		-0.15		-0.01		-0.09
		(1.46)		(-0.25)		(-0.06)		(-0.83)
Receivables		0.82**		-0.98		-0.08		-0.14
		(2.17)		(-1.32)		(-0.58)		(-0.95)
Inventory		-1.29***		-1.61***		-0.12		-0.25*
		(-3.53)		(-2.75)		(-1.02)		(-1.91)

Ln(Firm age)		0.03		0.14*		-0.02		-0.05**
		(0.49)		(1.74)		(-1.21)		(-2.52)
Constant	3.65***	-1.54***	3.59***	1.52**	0.97***	0.95***	0.85***	1.08***
	(24.71)	(-4.46)	(17.05)	(2.17)	(50.78)	(11.25)	(27.67)	(9.63)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	982	982	971	971	981	981	969	969

Panel B: Performance-related non-price terms

	(1) Financial covenants	(2) Financial covenants	(3) Performance pricing	(4) Performance pricing	(5) Warrants	(6) Warrants	(7) Convertible	(8) Convertible
Bank FCO	-0.15	-0.14	-0.11	-0.09	0.08	0.09*	-0.00	-0.02
	(-1.59)	(-1.45)	(-1.45)	(-1.20)	(1.54)	(1.72)	(-0.26)	(-1.55)
FCO	-0.27***	-0.18***	-0.33***	-0.26***	0.16***	0.11***	0.06**	0.05*
	(-4.18)	(-2.94)	(-12.35)	(-8.37)	(3.15)	(2.61)	(2.24)	(1.77)
Investment bank	-0.14*	-0.21***	-0.16**	-0.20***	0.07	0.09*	0.11**	0.12**
	(-1.67)	(-2.80)	(-2.41)	(-3.06)	(1.59)	(1.91)	(2.06)	(2.11)
PE/VC/BDC	-0.46***	-0.31***	-0.35***	-0.24***	0.46***	0.30***	0.18***	0.15***
	(-5.90)	(-3.81)	(-14.95)	(-7.76)	(6.51)	(4.15)	(3.39)	(2.64)
Hedge fund/IM	-0.57***	-0.45***	-0.34***	-0.23***	0.24***	0.17***	0.28***	0.23***
	(-8.27)	(-7.09)	(-12.51)	(-5.28)	(3.64)	(2.64)	(5.82)	(4.83)
Insurance	-0.06	0.02	-0.36***	-0.35***	0.13	0.09	-0.00	-0.01
	(-0.46)	(0.17)	(-12.16)	(-5.75)	(1.24)	(1.52)	(-0.36)	(-0.38)
Ln(Assets)		0.05***		0.06***		-0.01**		-0.01*
		(3.48)		(5.21)		(-2.22)		(-1.77)
Profitability		0.28***		0.03		-0.28***		-0.09
		(3.37)		(0.40)		(-3.76)		(-1.52)
Leverage		0.06		-0.13**		-0.00		0.05
		(0.96)		(-2.31)		(-0.04)		(1.40)
Research expense		0.05		-0.10)		0.18		-0.18*
		(0.31)		(-0.89)		(1.33)		(-1.81)
PP&E		-0.01		0.02		-0.03		-0.01
		(0.14)		(0.25)		(-0.88)		(-0.38)
Cash		0.06		0.02		0.07		-0.10
		(0.47)		(0.15)		(0.81)		(-1.57)
Receivables		0.48***		0.07		-0.28***		0.01
		(3.39)		(0.51)		(-3.37)		(0.21)
Inventory		-0.43***		-0.16		-0.14**		0.02
		(-3.84)		(-1.46)		(-2.08)		(0.38)
Ln(Firm age)		0.01		-0.02		0.00		-0.01
		(0.63)		(-0.88)		(0.07)		(-0.97)
Constant	0.85***	0.54***	0.29***	0.11	0.03*	0.18***	-0.00	0.13**
	(26.45)	(5.44)	(8.59)	(1.09)	(1.73)	(2.91)	(-0.08)	(2.12)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	983	983	983	983	981	981	981	981

Panel C: Other loan terms

	(1) Fixed rate loan	(2) Fixed rate loan	(3) Upfront fee (bp)	(4) Upfront fee (bp)	(5) Annual fee (bp)	(6) Annual fee (bp)	(7) Second lien	(8) Second lien
Bank FCO	0.16*	0.13	11.96	3.40	-0.90	-0.97	0.03	0.02
	(1.85)	(1.44)	(1.34)	(0.40)	(-0.80)	(-0.59)	(0.87)	(0.70)
FCO	0.29***	0.26***	31.14**	19.82	10.92	10.98	0.05*	0.06*
	(4.79)	(4.52)	(2.53)	(1.54)	(1.28)	(1.23)	(1.72)	(1.77)
Investment bank	0.26***	0.28***	67.72***	61.50**	-1.20	0.20	0.12*	0.12*
	(2.86)	(3.45)	(2.74)	(2.58)	(-1.98)	(0.18)	(1.66)	(1.74)
PE/VC/BDC	0.63***	0.56***	-1.99	-23.08*	-1.84***	-3.89**	0.04	0.07**
	(9.94)	(7.90)	(-0.21)	(-1.89)	(-3.43)	(-2.36)	(1.56)	(2.00)
Hedge fund/IM	0.76***	0.70***	22.75*	0.32	-0.18	-1.04	0.03	0.04
	(14.48)	(13.44)	(1.85)	(0.02)	(-0.14)	(-0.64)	(1.41)	(1.43)
Insurance	0.82***	0.76***	26.99	17.69	-2.18**	-3.10	-0.01*	-0.01
	(11.46)	(9.86)	(0.88)	(0.78)	(-2.26)	(-1.51)	(-1.88)	(-0.93)
Ln(Assets)		-0.03***		-6.00***		-0.96**		-0.00
		(-3.46)		(-3.54)		(-2.11)		(-0.63)
Profitability		-0.11		-28.87*		-2.05		0.05**
		(-1.58)		(-1.93)		(-0.78)		(2.04)
Leverage		0.01		17.06*		-0.43		0.02
		(0.19)		(1.73)		(-0.26)		(0.83)
Research expense		-0.06		-23.26		5.00		-0.01
		(-0.44)		(-1.25)		(0.87)		(-0.36)
PP&E		0.03		2.86		4.99		0.01
		(0.47)		(0.21)		(1.33)		(0.44)
Cash		-0.05		-14.46		-6.78		0.01
		(-0.44)		(-0.90)		(-1.45)		(0.21)
Receivables		-0.12		12.73		-4.18		-0.02
		(-1.28)		(0.64)		(-0.75)		(-0.66)
Inventory		0.03		-0.09		-0.25		0.03
		(0.43)		(-0.01)		(-0.05)		(0.60)
Ln(Firm age)		0.00		-0.59		1.27		0.01
		(0.21)		(-0.20)		(1.33)		(0.74)
Constant	0.05**	0.28***	22.45***	56.23***	4.59**	7.77**	0.01	-0.02
	(2.25)	(3.49)	(4.23)	(3.34)	(2.01-)	(2.22)	(0.46)	(-0.83)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	959	959	835	835	839	839	983	983

Table 7: Fuzzy RDD using the coverage error-rate-optimal bandwidth selector

The table reports the results of fuzzy RDD estimation using local linear polynomials for various outcome variables. The treatment is borrowing from a nonbank. The running variable is trailing twelve-month EBITDA, with a discontinuity at zero. The slope of the effect of the running variable on the probability of treatment is allowed to differ to the left and right of the discontinuity. The estimators are constructed using a triangular kernel. Symmetric bandwidths around zero are determined using the coverage error-rate-optimal (CER) bandwidth selector of Calonico et al. (2016). The CER bandwidth selector depends on the structure of all the data and must be re-estimated for each outcome variable. The table reports bandwidth, the number of observations included to the left and right of the discontinuity, the first-stage effect of an indicator for negative EBITDA on the treatment probability, and the second-stage estimate of the treatment effect on the outcome variables. *z*-statistics using bias-adjusted standard errors from Calonico et al. (2016) that adjust for clustering at the firm level are reported in parentheses. The following covariates are included, with coefficients omitted for brevity: the log of total assets, leverage, research expenses, PP&E, cash, receivables, inventory, the log of firm age, the year of loan origination, and industry effects. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Bandwidth	Left obs.	Right obs.	1st stage	2nd stage
Initial interest rate	28.66	177	300	-0.43***	480.61***
				(-5.46)	(4.37)
Ln(Amount)	31.13	191	348	-0.41***	-0.38
				(-5.64)	(-0.84)
Maturity	32.51	193	351	-0.41***	-1.49
				(-5.61)	(-1.40)
Seniority	41.28	200	404	-0.41***	-0.18
				(-5.95)	(-0.92)
Security	26.31	184	310	-0.43***	0.01
				(-5.72)	(0.25)
Second lien	23.18	180	301	-0.44***	-0.03
				(-5.65)	(-1.36)
Financial covenants	33.39	195	364	-0.40***	-0.45**
				(-5.59)	(-2.44)
Performance pricing	28.97	188	332	-0.41***	-0.07
				(-5.55)	(-0.52)
Warrants	21.45	175	288	-0.45***	0.38**
				(-5.63)	(2.45)
Convertible	28.79	186	331	-0.43***	0.14
				(-5.73)	(1.29)
Upfront fee	17.21	152	207	-0.42***	26.50
				(-4.89)	(0.79)
Annual fee	21.48	160	234	-0.43***	12.00
				(-5.01)	(1.32)
Bankrupt_{t+3}	22.85	161	275	-0.41***	-0.04
				(-4.98)	(-0.60)
$\Delta\ \text{Profitability}_{t+1}$	24.53	177	297	-0.40***	0.10
				(-5.08)	(0.93)
$\Delta\ \text{Profitability}_{t+2}$	21.56	160	254	-0.44***	0.03
				(-4.87)	(0.11)
$\Delta\ \text{Profitability}_{t+3}$	20.16	132	202	-0.42***	0.21*
				(-4.53)	(1.74)

Table 8: Matching estimates for loan characteristics

This table provides results of a nearest-neighbor matching using Mahalanobis distance between borrowers from nonbanks (*treated*) and banks (*control*). To create the control group, we utilize Mahalanobis matching with exact matching for loan origination year in addition to (nearest neighbor) matching on borrowing firm Profitability and Leverage. Panel A provides the covariate balance of the sample before and after the matching used to estimate the ATET for interest rates (as presented in the first column of Panel B). Panel B reports average treatment effect on the treated (ATET) with Abadie-Imbens (AI) robust standard errors in the parentheses for loan amount, initial interest rate, and maturity in Columns 1-3, respectively. The sample includes all borrowings of a random sample of 632 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level using the average value of each variable across the tranches in a deal. Initial interest rate is equal to the fixed rate for fixed rate loans and to 3-month LIBOR plus spread for floating rate loans. Variable definitions are in Appendix B. ATET is bias-adjusted by using firm size (Ln (Assets)), Profitability, Leverage, Research expense, PP&E, Cash, Receivables, Inventory, Ln (Firm Age). Symbols *, **, *** denote significance at the 10%, 5%, and 1% respectively.

Panel A: Covariate Balance after Matching

	Standardized Difference		Variance Ratio	
	Raw	Matched	Raw	Matched
Ln (Assets)	-0.521	-0.188	1.319	0.990
Profitability	-0.748	-0.100	3.206	1.195
Leverage	0.484	0.069	1.709	1.075
Research expense	0.286	-0.052	2.935	0.983
PP&E	-0.088	0.097	0.908	1.108
Cash	0.054	-0.049	1.527	0.834
Receivables	0.056	0.116	1.356	1.170
Inventory	-0.033	-0.192	0.954	0.599
Ln (Firm Age)	-0.342	-0.198	1.162	1.134

Panel B: Matching Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Interest Rate	Ln (Amount)	Seniority	Security	Financial Covenants	Warrants
ATET						
Nonbank Dummy	344.04***	-0.316**	-0.238***	-0.102***	-0.242***	0.020***
(AI robust *std. errors)*	(25.01)	(0.124)	(0.034)	(0.032)	(0.043)	(0.028)
N (Matched Observations)	578	604	604	604	604	604
Bias-adj. Variables	Ln (Assets), Profitability, Leverage, Research expense, PP&E, Cash, Receivables, Inventory, Ln (Firm Age)					

Table 9: Probability of bankruptcy for bank versus nonbank loans

This table reports estimates from a linear probability model of borrower's bankruptcy over the three years after loan origination. The sample includes all borrowings of a random sample of 632 middle-market firms originated during the 2010-2014 period. Bankruptcy dates as of December 31, 2017 are from Capital IQ. There are 43 deals by 24 borrowers that result in bankruptcy within three years. Observations are aggregated to the deal level using the average value of each variable across the tranches in a deal. Variable definitions are in Appendix B. Industry fixed effects are based on Fama-French 12 industries. *z*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)
Nonbank	0.04**	0.03	0.03	0.03
	(2.01)	(1.50)	(1.21)	(1.16)
Ln(Assets)		0.00	0.00	0.01
		(0.65)	(0.20)	(0.81)
EBITDA		-0.09**	-0.10**	-0.16*
		(-2.42)	(-2.32)	(-1.84)
Leverage			0.02	-0.02
			(0.60)	(-0.50)
PP&E			0.02	0.02
			(0.50)	(0.48)
Cash			0.07	0.12
			(0.93)	(1.41)
Receivables			-0.03	0.04
			(-0.34)	(0.38)
Inventory			-0.05	-0.01
			(-0.75)	(-0.10)
Research expense			-0.05	-0.10
			(-0.71)	(-0.97)
Ln(Firm age)			0.01	0.00
			(0.48)	(0.24)
Volatility				0.06
				(1.43)
Sales growth				0.01
				(0.26)
Market-to-book				-0.01
				(-1.20)
Constant	0.01	-0.02	-0.03	-0.09
	(0.31)	(-0.68)	(-0.41)	(-0.91)
Year effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Observations	938	901	892	696

Table 10: Future performance by lender type

This table reports the results of regressions of borrower's future performance on lender type indicators and borrower characteristics. Panels A and B show the results for changes in profitability while Panels C and D show the results for stock returns starting thirty days after loan origination. Stock returns include delisting returns; after delisting, proceeds are not reinvested. The sample includes all borrowings of a random sample of 632 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level using the average value of each variable across the tranches in a deal. Variable definitions are in Appendix B. Industry fixed effects are based on Fama-French 12 industries. *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

Panel A: Year-to-year changes in profitability for nonbanks vs. banks

	(1) [*t*,*t*+1]	(2) [*t*+*1*,*t*+2]	(3) [*t*+*2*,*t*+3]	(4) [*t*,*t*+1]	(5) [*t*+*1*,*t*+2]	(6) [*t*+*2*,*t*+3]
Nonbank	-0.03***	-0.01	0.00	0.00	-0.01	-0.01
	(-2.63)	(-1.17)	(0.23)	(0.39)	(-1.26)	(-1.08)
Ln(Assets)	0.00	0.00	-0.00	0.00	0.00	-0.00
	(0.24)	(1.28)	(-0.90)	(0.85)	(0.96)	(-0.60)
Profitability_t	-0.49***	-0.08*	-0.01	-0.32***	-0.13**	0.01
	(-8.79)	(-1.72)	(-0.28)	(-5.03)	(-2.22)	(0.24)
Leverage	0.07**	0.02	-0.00	0.04*	0.01	-0.00
	(2.39)	(1.03)	(-0.17)	(1.78)	(0.50)	(-0.15)
Research expense	0.02	-0.12	-0.10	0.11	-0.25**	0.05
	(0.15)	(-1.49)	(-1.31)	(1.00)	(-2.26)	(0.58)
PP&E	0.00	0.03	-0.01	0.01	0.03	-0.01
	(0.06)	(1.10)	(-0.25)	(0.84)	(1.48)	(-0.61)
Cash	-0.12**	-0.01	-0.08	-0.08	-0.06	-0.02
	(-2.02)	(-0.16)	(-1.49)	(-1.64)	(-1.38)	(-0.31)
Receivables	-0.04	0.07	0.02	-0.01	0.01	-0.00
	(-0.68)	(1.54)	(0.42)	(-0.31)	(0.17)	(-0.03)
Inventory	-0.08**	0.05*	-0.01	0.02	-0.00	-0.01
	(-2.22)	(1.86)	(-0.11)	(0.74)	(-0.18)	(-0.51)
Ln(Firm age)	0.01	-0.00	-0.00	0.01*	0.00	0.00
	(1.30)	(-0.33)	(-0.28)	(1.81)	(0.21)	(0.90)
Volatility				-0.04**	-0.01	0.00
				(-2.09)	(-0.37)	(0.11)
Sales growth				-0.03	0.02	0.04*
				(-1.26)	(0.77)	(1.95)
Market-to-book				0.01	-0.00	-0.01*
				(1.17)	(-0.05)	(-1.86)
Constant	0.04	-0.05	0.05	-0.00	0.01	0.01
	(1.18)	(-1.45)	(1.24)	(-0.04)	(0.28)	(0.15)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	956	878	743	757	701	586

Panel B: Year-to-year changes in profitability for different lender types

	(1)	(2)	(3)	(4)	(5)	(6)
	[*t*,*t*+1]	[*t*+*1*,*t*+2]	[*t*+*2*,*t*+3]	[*t*,*t*+1]	[*t*+*1*,*t*+2]	[*t*+*2*,*t*+3]
Bank FCO	-0.01	0.01	0.00	0.00	-0.01	0.00
	(-0.44)	(0.75)	(0.05)	(0.31)	(-0.67)	(0.22)
FCO	-0.05***	-0.02	-0.01	-0.01	-0.01	-0.00
	(-2.82)	(-0.83)	(-0.41)	(-0.88)	(-0.90)	(-0.19)
Investment bank	-0.00	-0.02	0.02	0.01	-0.01	0.00
	(-0.12)	(-1.11)	(1.23)	(0.66)	(-0.84)	(0.32)
PE/VC/BDC	0.01	-0.04	-0.03	0.04	-0.03	-0.05
	(0.34)	(-1.55)	(-0.79)	(1.29)	(-0.94)	(-1.12)
Hedge fund/IM	-0.06*	-0.01	0.03	0.00	-0.01	-0.03
	(-1.95)	(-0.31)	(0.69)	(0.14)	(-0.23)	(-1.20)
Ln(Assets)	0.00	0.00	-0.01	0.00	0.00	-0.00
	(0.95)	(0.89)	(-1.09)	(0.97)	(0.85)	(-0.76)
Profitability$_t$	-0.46***	-0.10*	-0.02	-0.30***	-0.14**	-0.01
	(-8.45)	(-1.93)	(-0.42)	(-4.91)	(-2.29)	(-0.13)
Leverage	0.06**	0.03	-0.01	0.04*	0.01	-0.01
	(2.04)	(1.11)	(-0.27)	(1.73)	(0.40)	(-0.29)
Research expense	0.04	-0.12	-0.09	0.10	-0.24**	0.06
	(0.39)	(-1.50)	(-1.12)	(0.89)	(-2.17)	(0.64)
PP&E	0.00	0.02	-0.01	0.01	0.04	-0.01
	(0.08)	(0.94)	(-0.40)	(0.82)	(1.57)	(-0.55)
Cash	-0.13**	-0.01	-0.08	-0.07	-0.06	-0.02
	(-2.18)	(-0.16)	(-1.42)	(-1.52)	(-1.44)	(-0.43)
Receivables	-0.02	0.07	0.02	-0.02	0.01	-0.00
	(-0.43)	(1.45)	(0.32)	(-0.42)	(0.21)	(-0.05)
Inventory	-0.06	0.04	-0.02	0.03	-0.01	-0.02
	(-1.59)	(1.39)	(-0.38)	(1.03)	(-0.25)	(-0.76)
Ln(Firm age)	0.00	-0.00	-0.00	0.01*	0.00	0.01
	(0.99)	(-0.12)	(-0.16)	(1.74)	(0.43)	(0.93)
Volatility				-0.04**	-0.01	0.01
				(-2.07)	(-0.37)	(0.27)
Sales growth				-0.03	0.02	0.04**
				(-1.48)	(0.84)	(2.12)
Market-to-book				0.01	-0.00	-0.01
				(0.95)	(-0.11)	(-1.53)
Constant	0.03	-0.04	0.06	-0.00	0.01	0.01
	(0.73)	(-1.23)	(1.34)	(-0.12)	(0.24)	(0.28)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	938	861	728	743	688	574

Panel C: Subsequent stock returns for nonbanks vs. banks

	(1)	(2)	(3)	(4)	(5)	(6)
Return period:	[*t*, *t*+1]	[*t*+1, *t*+2]	[*t*+2, *t*+3]	[*t*, *t*+1]	[*t*+1, *t*+2]	[*t*+2, *t*+3]
Nonbank	-0.01	0.03	-0.01	0.02	-0.01	-0.01
	(-0.07)	(0.45)	(-0.22)	(0.27)	(-0.12)	(-0.20)
Ln(Assets)	0.00	0.06***	0.02	0.00	0.06**	0.03
	(0.15)	(2.73)	(1.29)	(0.18)	(2.44)	(1.15)
Profitability$_t$	0.43**	0.25	0.04	0.49**	0.36**	-0.01
	(2.10)	(1.64)	(0.18)	(2.16)	(2.06)	(-0.04)
Leverage	0.14	0.08	-0.11	0.16	0.16	-0.12
	(0.89)	(0.60)	(-0.84)	(1.03)	(1.17)	(-0.76)
Research expense	0.53	0.47	0.60	0.48	0.72**	0.57
	(1.47)	(1.58)	(1.30)	(1.27)	(2.49)	(1.21)
PP&E	-0.25**	0.04	-0.19*	-0.23**	0.05	-0.18
	(-2.13)	(0.34)	(-1.77)	(-2.00)	(0.39)	(-1.60)
Cash	-0.35*	0.14	-0.16	-0.52***	0.16	-0.03
	(-1.71)	(0.66)	(-0.59)	(-2.63)	(0.80)	(-0.10)
Receivables	-0.07	0.47	0.13	-0.13	0.51*	0.13
	(-0.25)	(1.63)	(0.55)	(-0.47)	(1.74)	(0.53)
Inventory	-0.19	0.22	-0.27*	-0.14	0.24	-0.30**
	(-1.03)	(1.08)	(-1.87)	(-0.75)	(1.19)	(-2.02)
Ln(Firm age)	0.02	0.02	0.07***	0.01	-0.00	0.06*
	(0.66)	(0.55)	(2.68)	(0.32)	(-0.03)	(1.95)
Volatility				-0.01	-0.03	0.03
				(-0.07)	(-0.26)	(0.41)
Sales growth				-0.04	-0.07	0.03
				(-0.40)	(-0.65)	(0.30)
Market-to-book				0.00	-0.04*	-0.01
				(0.03)	(-1.73)	(-0.46)
Constant	0.01	-0.40**	-0.05	0.10	-0.29	-0.05
	(0.04)	(-2.03)	(-0.29)	(0.38)	(-1.10)	(-0.20)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	828	828	828	775	775	775

Panel D: Subsequent stock returns for different lender types

	(1)	(2)	(3)	(4)	(5)	(6)
Return period:	[*t*, *t*+1]	[*t*+1, *t*+2]	[*t*+2, *t*+3]	[*t*, *t*+1]	[*t*+1, *t*+2]	[*t*+2, *t*+3]
Bank FCO	0.06	0.01	-0.08	0.05	-0.05	-0.08
	(0.30)	(0.12)	(-0.81)	(0.25)	(-0.44)	(-0.80)
FCO	0.07	0.06	0.05	0.09	0.03	0.02
	(0.67)	(0.65)	(0.44)	(0.86)	(0.34)	(0.20)
Investment bank	0.01	0.24	0.06	-0.02	0.25	0.06
	(0.10)	(1.32)	(0.72)	(-0.12)	(1.46)	(0.77)
PE/VC/BDC	-0.21*	-0.16	-0.16	-0.22	-0.25*	-0.10
	(-1.70)	(-1.10)	(-1.24)	(-1.55)	(-1.85)	(-0.69)
Hedge fund/IM	0.03	-0.10	-0.06	0.11	-0.12	-0.08
	(0.21)	(-0.92)	(-0.66)	(0.67)	(-0.97)	(-0.76)
Ln(Assets)	0.00	0.05**	0.02	0.00	0.05**	0.02
	(0.10)	(2.24)	(0.96)	(0.00)	(2.06)	(0.85)
Profitability_t	0.37*	0.17	-0.01	0.43*	0.27	-0.05
	(1.79)	(1.14)	(-0.03)	(1.86)	(1.52)	(-0.18)
Leverage	0.10	0.09	-0.11	0.14	0.16	-0.11
	(0.66)	(0.69)	(-0.80)	(0.95)	(1.16)	(-0.73)
Research expense	0.61*	0.51*	0.64	0.56	0.79***	0.59
	(1.69)	(1.76)	(1.42)	(1.51)	(2.78)	(1.28)
PP&E	-0.23*	0.02	-0.18*	-0.22*	0.03	-0.17
	(-1.84)	(0.17)	(-1.66)	(-1.80)	(0.26)	(-1.49)
Cash	-0.36*	0.11	-0.18	-0.55***	0.12	-0.05
	(-1.78)	(0.54)	(-0.66)	(-2.76)	(0.58)	(-0.18)
Receivables	-0.06	0.52*	0.14	-0.11	0.55*	0.13
	(-0.22)	(1.81)	(0.59)	(-0.37)	(1.90)	(0.52)
Inventory	-0.18	0.20	-0.29*	-0.16	0.23	-0.32**
	(-0.96)	(0.99)	(-1.93)	(-0.86)	(1.13)	(-2.06)
Ln(Firm age)	0.02	0.02	0.07**	0.02	-0.00	0.06*
	(0.64)	(0.53)	(2.55)	(0.47)	(-0.00)	(1.86)
Volatility				-0.03	-0.02	0.03
				(-0.22)	(-0.21)	(0.37)
Sales growth				-0.01	-0.05	0.04
				(-0.10)	(-0.44)	(0.41)
Market-to-book				0.00	-0.04*	-0.01
				(0.11)	(-1.72)	(-0.53)
Constant	0.03	-0.35*	-0.02	0.12	-0.24	-0.01
	(0.13)	(-1.84)	(-0.11)	(0.47)	(-0.96)	(-0.03)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	811	811	811	760	760	760

Table 11: Announcement returns around loan origination

This table reports the results of regressions of cumulative announcement returns around loan origination. Market adjusted cumulative returns (expressed in percent) are calculated from loan origination through one day after the SEC filing disclosing the terms of the new loan. Sample is limited to loans for which filing is within five calendar days of loan origination and for which the last stock price before loan origination is at least $1. Heteroscedasticity robust *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)
Nonbank	3.568**	3.406***	2.926**
	(2.53)	(2.60)	(2.40)
EBITDA < 0		-0.157	-0.342
		(-0.09)	(-0.14)
Ln(Assets)		-0.282	-0.428
		(-0.67)	(-0.87)
Market-to-book			-0.153
			(-0.56)
Leverage			3.719
			(1.06)
Profitability			-3.071
			(-0.90)
Ln(Firm age)			0.281
			(0.54)
Constant	0.663**	2.306	2.017
	(1.98)	(0.91)	(0.65)
Observations	378	371	357

Table 12: Local banking markets and propensity to borrow from nonbanks

This table reports the results of linear probability models of the propensity to borrow from a nonbank lender on the characteristics of the county in which the firm's headquarters are located. Bank leverage is the deposit-weighted average of the tier 1 leverage ratio of the bank holding companies with branches in the county of firm's headquarters. Deposit concentration is the Herfindahl-Hirschman Index of the concentration of deposit in the county of firm's headquarters. Deposits within a county are aggregated across multiple banks owned by the same bank holding company. Personal income growth is the one-year growth rate in county-level per capita personal income. All explanatory variables are as of the year prior to loan origination. Industry fixed effects are based on Fama-French 17 industries. *t*-statistics adjusted for clustering by county are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank leverage ratio	-0.051***	-0.080***	-0.070***	-0.083***	-0.061***	-0.068***	-0.070***	-0.056**
	(-2.64)	(-3.64)	(-3.16)	(-3.21)	(-2.66)	(-3.06)	(-3.12)	(-2.41)
Deposit concentration	-0.331**	-0.438***	-0.359**	-0.339**	-0.354**	-0.357**	-0.358**	-0.348**
	(-2.16)	(-2.76)	(-2.27)	(-2.12)	(-2.24)	(-2.25)	(-2.26)	(-2.19)
Ln(Total deposits)				-0.013				
				(-0.98)				
Ln(Personal income)					0.065			0.080
					(1.20)			(1.36)
Personal income growth						0.383		0.283
						(0.77)		(0.56)
Unemployment rate							0.003	0.008
							(0.31)	(0.85)
Year effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1004	1006	1004	1004	1004	1004	1004	1004

Internet Appendix

This Internet Appendix first discusses results from a cluster analysis to determine which lender types can be grouped together and which types should be viewed as distinct. Second, the Internet Appendix provides further diagnostics to examine the validity of the regression discontinuity design.

A.1 Cluster analysis

Cluster analysis provides an agnostic way of grouping individuals in a population based on observable characteristics. Specifically, we employ *k*-medians clustering, which uses an iterative, data-driven process to partition the data into *k* clusters organized around *k* centroids. A conceptually attractive feature of cluster analysis is that it does not allow the researcher to hypothesize which observations should be grouped together. Hence, cluster analysis can be used to obtain an additional look at which types of lenders behave similarly without being biased by the researcher's priors. A significant disadvantage of cluster analysis is that the researcher must decide how many clusters there are in the data.

K-medians clustering proceeds as follows. First, *k* observations are chosen at random as the initial cluster centroids. All observations in the sample are assigned to the cluster with the closest centroid based on the Manhattan distance. Next, the median of the observations in each cluster is calculated and becomes the new cluster center. Observations are reassigned to a different cluster if they are closer to the recalculated center of that cluster. These steps are repeated until additional iterations fail to produce any change in cluster composition. Because this process finds a local optimum that is contingent on the initially chosen centroids, we re-initiate the estimation 5,000 times and retain the solution with the lowest sum of absolute deviations (SAD) from the cluster center.

We assign deals to clusters based on the following loan and firm characteristics: deal size, maturity, whether or not the loan charges a fixed interest rate, the initial interest rate, whether or not the loan is senior, whether it is secured by a first lien, second lien, or unsecured, as well as the borrower's EBITDA, leverage, and total assets in 2015 US dollars. We first turn to the choice of *k*. The elbow method can be used as a heuristic to determine the "optimal" number of clusters. The elbow method consists of plotting the sum of absolute deviations for $k = 1$ through n clusters.[15] If there are, e.g., four sharply distinct clusters in the data, the sum of absolute deviations will fall until $k = 4$ at which point there will be a kink in the SAD function and it will level off. Graphically, the kink resembles an elbow. Note that the SAD function will continue to fall as more clusters are added since, by construction, SAD equals zero if the number of clusters equals the number of observations. We search for an elbow for up to ten clusters. Figure A1 shows the result. Due to computational limitations, we use 500 cluster initiations for each k when producing these graphs.

The top left graph in Figure A1 plots the sum of absolute deviations. The top right graph plots the natural log of the SAD. The bottom left graph plots η^2, which is the percentage reduction in SAD from the one-cluster solution to the k-cluster solution. The bottom right graph plots *PRE*, which is the additional percentage reduction in SAD obtained by adding the k^{th} cluster. It is obvious from Figure A1 that there is no elbow in the SAD function. This indicates there is no set number of clusters that are compact internally and distant from each other. This is perhaps not surprising given that a wide range of firm types can use multiple types of loans such as senior secured, junior, long and short maturity, etc. Nevertheless, it is instructive to see which lenders' loans the algorithm determines to be similar to each other as one increases the number of clusters. The *PRE* function levels off somewhat after four clusters, and adding clusters beyond six results in little improvement. Thus, for the sake of brevity, we choose to inspect the solutions for $k = 4$, 5, and 6.

Panel A of Table A1 shows the four-cluster solution and Panel A of Table A2 shows loan and firm characteristics for the clusters. There are three clusters dominated by banks and one cluster dominated by nonbanks. Cluster one consists of medium sized secured floating rate loans to moderately profitable firms. Cluster two consists of very large senior secured floating rate loans, almost always with financial covenants, to large, profitable borrowers. Cluster three consists of large senior unsecured loans that are mostly floating rate and are extended to profitable borrowers with leverage and high current ratios. Cluster four consists entirely of fixed rate loans with an average interest rate of 9.2% and borrowers on average are unprofitable. Cluster four has the highest likelihood to include warrants and be convertible into equity and the lowest likelihood to include financial covenants. The vast majority of loans made by asset managers such as BDCs,

[15] The following analysis is analogue to Makles (2012), who describes the elbow method for *k*-means clustering.

hedge funds, investment managers, and PE/VCs are grouped into cluster four, with some observations in cluster one. Bank-affiliated finance companies as well as unaffiliated finance companies are spread throughout the clusters, but have around half of their observations in cluster one. Investment banks cluster especially into large loans (cluster two).

Panels B of Tables A1 and A2 show the five-cluster solution with characteristics. The bank-dominated clusters two and three show little change compared to the four-cluster solution (they are now labeled clusters one and four). The algorithm creates an additional cluster by more cleanly separating nonbank loans from bank loans. Clusters two and five are now dominated by asset managers with the main difference that cluster two contains senior loans and cluster five contains junior loans. Investment managers appear to prefer junior loans while PE/VC firms appear to have a slight preference for senior loans.

Panels C of Tables A1 and A2 show the six-cluster solution and corresponding characteristics. There is little change in the asset manager-dominated clusters (now labeled clusters one and five). The bank-dominated clusters have been rearranged to create one cluster consisting of very large senior secured floating rate loans with financial covenants entered into by banks and investment banks. Clusters two, four and six are dominated by senior secured floating rate bank loans, differing mainly in the size of the loans. Cluster three contains unsecured bank loans to high quality borrowers that pay low interest rates.

In summary, it appears that there are two clusters dominated by asset managers. Investment banks are unique in that they focus on large loans. Finance companies and bank finance companies are active across all clusters, with less activity among the largest loans.

We also examine the results of cluster analysis after excluding all bank loans from the sample in an effort to avoid making bank loans the anchor of a large number of clusters. Figure A2 shows the level and improvement in the objective function as one adds clusters. There is again no “elbow” in the object function, but the incremental improvement function levels off after four clusters. For the sake of brevity, we only discuss the four-cluster solution. Panels D of Tables A1 and A2 show that results are consistent with clustering including the bank loans. There are again two clusters of loans that are dominated by the asset managers and have a high probability of having warrants or being convertible to equity. The other two clusters are more akin to traditional bank loans in that they are mostly senior secured floating rate loans with a higher probability of having financial covenants. One cluster contains the larger loans, which are primarily made by investment banks. The other cluster contains smaller loans primarily made by finance companies and bank-affiliated finance companies. We again observe that finance companies are active across all clusters. Bank-affiliated finance companies appear to prefer the moderately sized senior secured floating rate loans in cluster three.

The analysis thus far yields four lender groups: banks, finance companies, investment banks, and asset managers. However, it is not clear whether bank-affiliated finance companies should be grouped with unaffiliated finance companies and whether there are distinctions among the asset managers that are masked by the cluster summary statistics. Next, we test whether these lenders should be grouped together or separately.

Table A3 reports tests for differences across the aforementioned lender types. Covariates are standardized to have a mean of zero and a standard deviation of one to allow for easy comparison of which covariates are economically most important. Column 1 compares bank FCOs to banks. Bank FCOs are more likely to make junior loans with a fixed interest rate and their borrowers have higher leverage. Column 2 compares Bank FCOs to unaffiliated FCOs. Their borrowers and loan structure appear similar, but Bank FCOs charge substantially lower interest rates. In light of this evidence, we treat Bank FCOs as a separate category of lender that is neither equivalent to banks nor equivalent to unaffiliated FCOs.

Columns 3 through 6 assess which of the asset managers are similar to each other so they can be grouped together. While all four types of vehicles have organizational differences, both BDCs and investment managers have fewer than thirty observations each, necessitating grouping them with other lenders. In each column, we split one of the lender types from the group of asset managers and test whether and how they differ from the other vehicles. Hedge funds engage in deals with more highly leveraged firms. Investment managers prefer senior unsecured debt. PE and VC firms make prefer less levered borrowers. BDCs prioritize secured loans to les leveraged borrowers. We use two criteria to determine whether and which lenders can be grouped together: First, if one type of lender is significantly different from the other asset managers along a certain dimension, the other type of lender cannot be significantly different with the opposite sign. Second, while the paucity of observations may reduce statistical power, we check for which types of lenders the estimation most often results in the same coefficient signs. The first criterion suggests that hedge funds and PE/VC firms cannot be grouped with each other due to significant differences in their borrowers' leverage. In addition, investment managers and BDCs cannot be grouped together due to strongly opposite preferences on borrowers' research intensity. The second criterion suggests that hedge funds and investment managers are most similar to each other and PE/VC firms and BDCs are most similar to each other as these are the only for which at least half of the coefficients have the same sign. Thus, while the overlap is not perfect, we group BDCs with PE/VC firms and investment managers with hedge funds. Column 7 tests whether these two groups are indeed significantly different from each other. Hedge funds and investment managers are significantly more likely to make senior unsecured loans than PE firms, VCs and BDCs. In addition, PE firms, VCs and BDCs target borrowers with lower leverage, higher research intensity and larger sales growth.

A.2 Regression discontinuity design

In this section, we show figures that zoom in closer to the boundary of zero EBITDA. We also formally test whether there is a discontinuity in the probability of borrowing from a nonbank around an EBITDA of zero and whether such discontinuity is stable when choosing different neighborhoods. In addition, we test whether borrowers manipulate EBITDA around the threshold, and whether there are discontinuities in the covariates.

Figure A3 shows the fraction of loans obtained from nonbank lenders by sample borrowers whose EBITDA is within an interval of ten million dollars around zero. We continue to find a strong discontinuity in the probability of borrowing from a nonbank. Firms with an EBITDA just above zero have roughly a 20% probability of borrowing from a nonbank. For firms with an EBITDA just below zero, the probability jumps to more than 60%.

Following the discussion in Gelman and Imbens (2014), in Table A4 we fit a local linear polynomial allowing for a different slope of in the relation between the EBITDA and the probability of nonbank lending to the right and to the left of an EBITDA of zero. An indicator that equals one if EBITDA is below zero tests for whether a discontinuity exists. We start with a neighborhood of \$100 million around zero EBITDA, then reduce the bandwidth to \$50 million, \$25 million, \$10 million, and \$5 million, respectively. EBITDA itself negatively predicts nonbank borrowing over the largest bandwidth. Regardless of choice of bandwidth, the discontinuity in the probability of nonbank borrowing is consistently around 40% and strongly significant.

A key concern in regression discontinuity designs is that subjects may manipulate the running variable to influence whether or not they will be assigned to the treatment group. Such concerns can be tested for by ensuring that the empirical distribution of the running variable is smooth across the boundary and by testing for discontinuities in observable covariates across the boundary. Figure A4 shows results from a test for discontinuity in the EBITDA distribution using the results for local polynomial density estimators in Cattaneo, Jansson, and Ma (2017a) and the companion Stata program described in Cattaneo, Jansson, and Ma (2017b). Following the default set by Cattaneo, Jansson, and Ma (2017b), we use local quadratic functions to generate separately smoothed point estimates for the distribution of EBITDA to the left and right of zero and local cubic functions to construct bias-corrected 95% confidence intervals. As can be seen from Figure A4, the confidence intervals coming from the left and from the right of zero strongly overlap. A test of the null hypothesis that the distribution is smooth across the zero EBITDA boundary produces an insignificant *t*-statistic of -0.03. This result is inconsistent with the concern that borrowers might precisely manipulate EBITDA to avoid having to borrow from a nonbank.

In Figure A5, we inspect the behavior of firm characteristics across the zero EBITDA boundary. To do so, we fit local linear functions within a range of plus or minus $10 million in EBITDA. For most of the covariates, it is clear that there is no discontinuity across the boundary as the bin means and the regression functions meet each other closely at the boundary. It is less clear whether cash holdings and sales growth are or are not discontinuous. In Table A5, we formally test for a discontinuity in the covariates. For each covariate, the table presents two local linear regressions: one regression restricting the sample to plus/minus $10 million in EBITDA and one regression further restricting the sample to plus/minus $5 million in EBITDA. When using a bandwidth of $10 million, we find a significant discontinuity in firm's cash holdings, which are larger among positive cash flow firms. There could be a discontinuity in sales growth, but it is significant only at the 10% level. Focusing on the narrowest bandwidth of $5 million, only the discontinuity in cash holdings persist. Note that cash holdings are measured by the cash-to-assets ratio and firms closer to the boundary are known to be smaller (Figure A5). It does not seem surprising that among small firms, those with positive cash flow are able to hold more cash than those with negative cash flow. Thus, we conclude that firms close to the zero cash flow boundary do not appear systematically different other than through cash flow itself.

In Table A6, we abandon the kernel density estimators used in the main part of the paper and instead implement the regression discontinuity design for interest rates over various ad hoc neighborhoods using simple two-stage least squares estimation. Here, the negative EBITDA indicator serves as an instrument for borrowing from a nonbank. We continue to find a large positive coefficient for the effect of borrowing from a nonbank on the interest rate paid on the loan. For the bandwidth of $25 million, which is most similar to the data-driven bandwidth in Table 7 of $28.66, results are almost identical to those obtained in Table 7.

Internet Appendix References

Cattaneo, Matias D., Michael Jansson, and Xinwei Ma, 2017a, Simple Local Polynomial Density Estimators, *University of Michigan Working Paper.*

Cattaneo, Matias D., Michael Jansson, and Xinwei Ma, 2017b, rddensity: Manipulation Testing Based on Density Discontinuity, *The Stata Journal, forthcoming.*

Makles, Anna, 2012, Stata tip 110: How to get the optimal k-means cluster solution, *The Stata Journal* 12, 347-351.

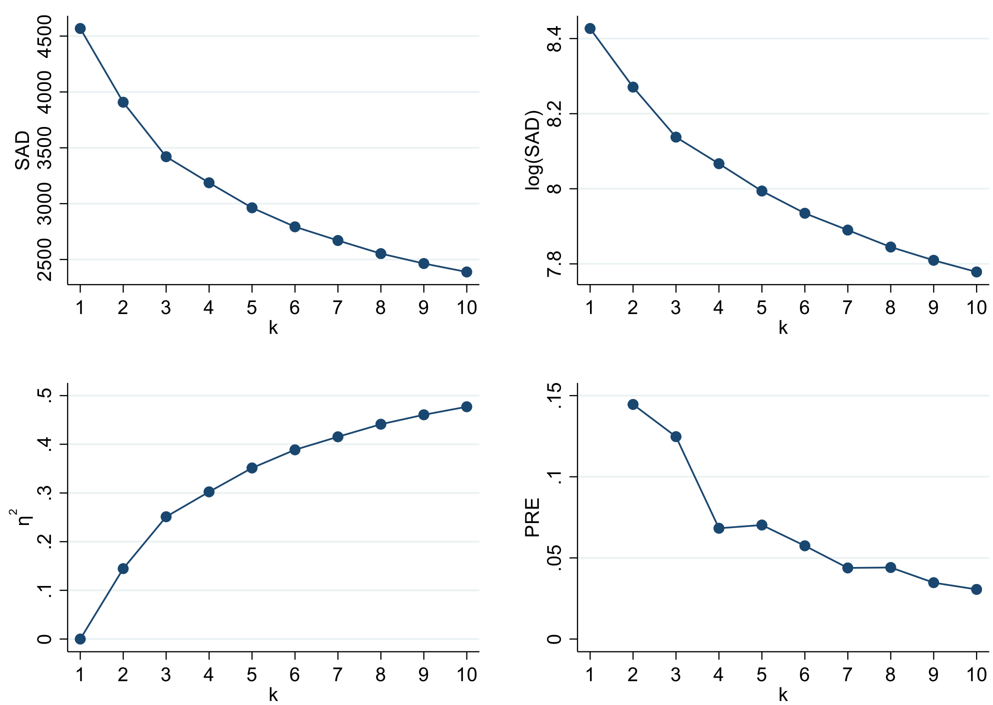

Figure A1: Improvement in the objective function with increasing *k* (all loans)

This figure shows the level and improvement in the objective function of the *k*-medians cluster analysis for different choices of *k*. All sample loan observations are clustered based on deal size, maturity, whether or not the loan charges a fixed interest rate, the initial interest rate, whether or not the loan is senior, whether it is secured by a first lien, second lien, or unsecured, as well as the borrower's EBITDA, leverage, and total assets in 2015 US dollars. The figure shows the sum of absolute deviations (top left), the natural log of the SAD (top right), η^2, the percentage reduction in SAD from the one-cluster solution to the *k*-cluster solution (bottom left), and *PRE*, the additional percentage reduction in SAD obtained by adding the k^{th} cluster (bottom right).

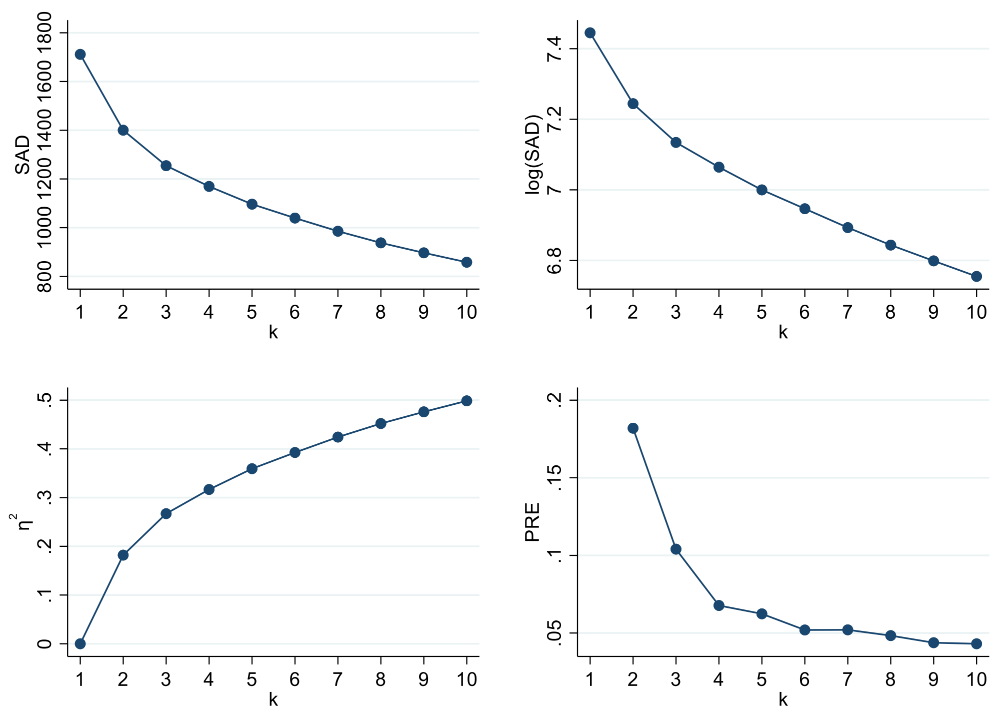

Figure A2: Improvement in the objective function with increasing *k* (excluding bank loans)

This figure shows the level and improvement in the objective function of the *k*-medians cluster analysis for different choices of *k* after excluding bank loans from the sample. Nonbank loan observations are clustered based on deal size, maturity, whether or not the loan charges a fixed interest rate, the initial interest rate, whether or not the loan is senior, whether it is secured by a first lien, second lien, or unsecured, as well as the borrower's EBITDA, leverage, and total assets in 2015 US dollars. The figure shows the sum of absolute deviations (top left), the natural log of the SAD (top right), η^2, the percentage reduction in SAD from the one-cluster solution to the *k*-cluster solution (bottom left), and *PRE*, the additional percentage reduction in SAD obtained by adding the k^{th} cluster (bottom right).

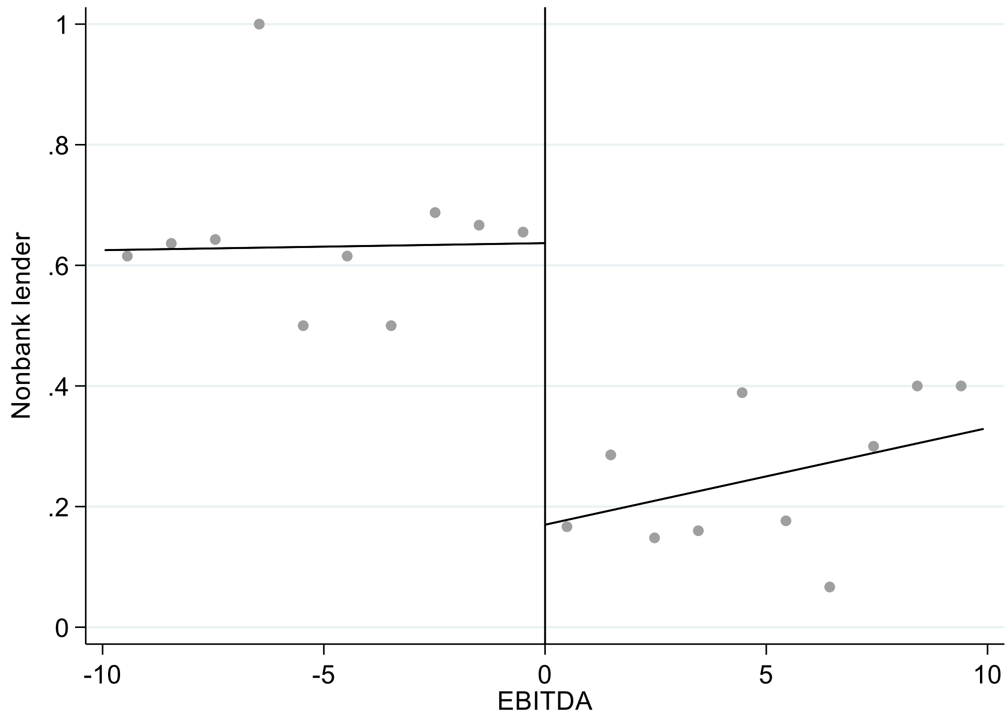

Figure A3: Fraction of loans obtained from nonbanks around the zero EBITDA boundary
This figure shows what fraction of loans is obtained from nonbanks by borrowers whose trailing twelve month EBITDA is between minus $10 million and plus $10 million. Ten even spaced bins are created on either side of the boundary.

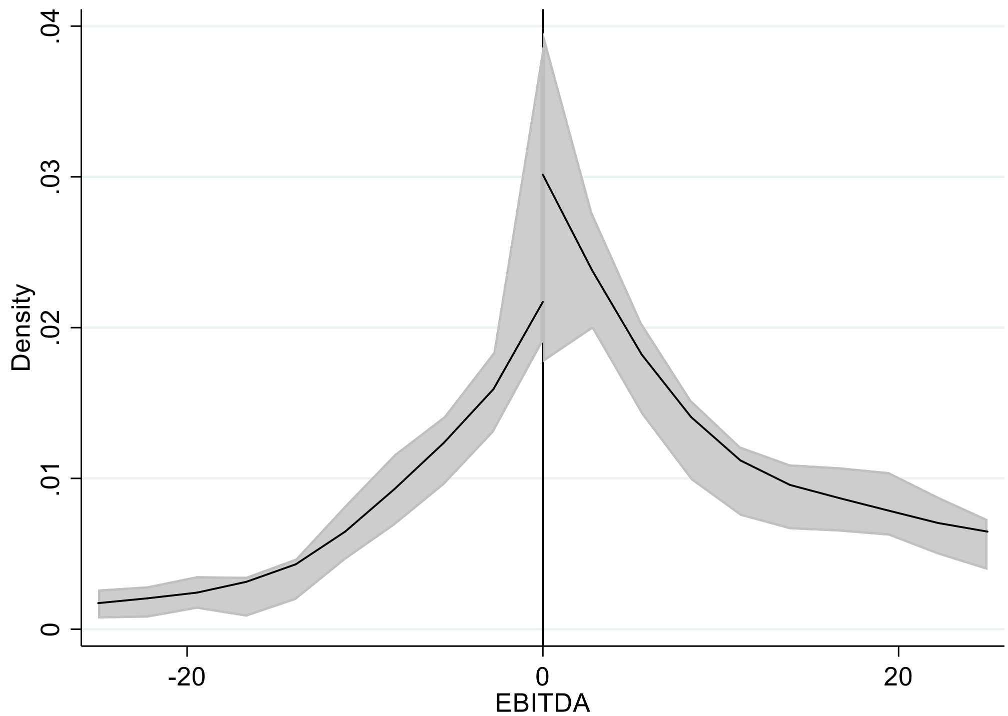

Figure A4: Test for discontinuity in the EBITDA distribution around the zero boundary
This figure shows results from a test for discontinuity in the EBITDA distribution using the results for local polynomial density estimators in Cattaneo, Jansson, and Ma (2017a). The test uses a local quadratic function to generate point estimates and a local cubic function to construct bias-corrected 95% confidence intervals. A bandwidth of $10 million in EBITDA is used. The *t*-statistic testing whether the heights of the distribution left and right of zero are different at the boundary is -0.03.

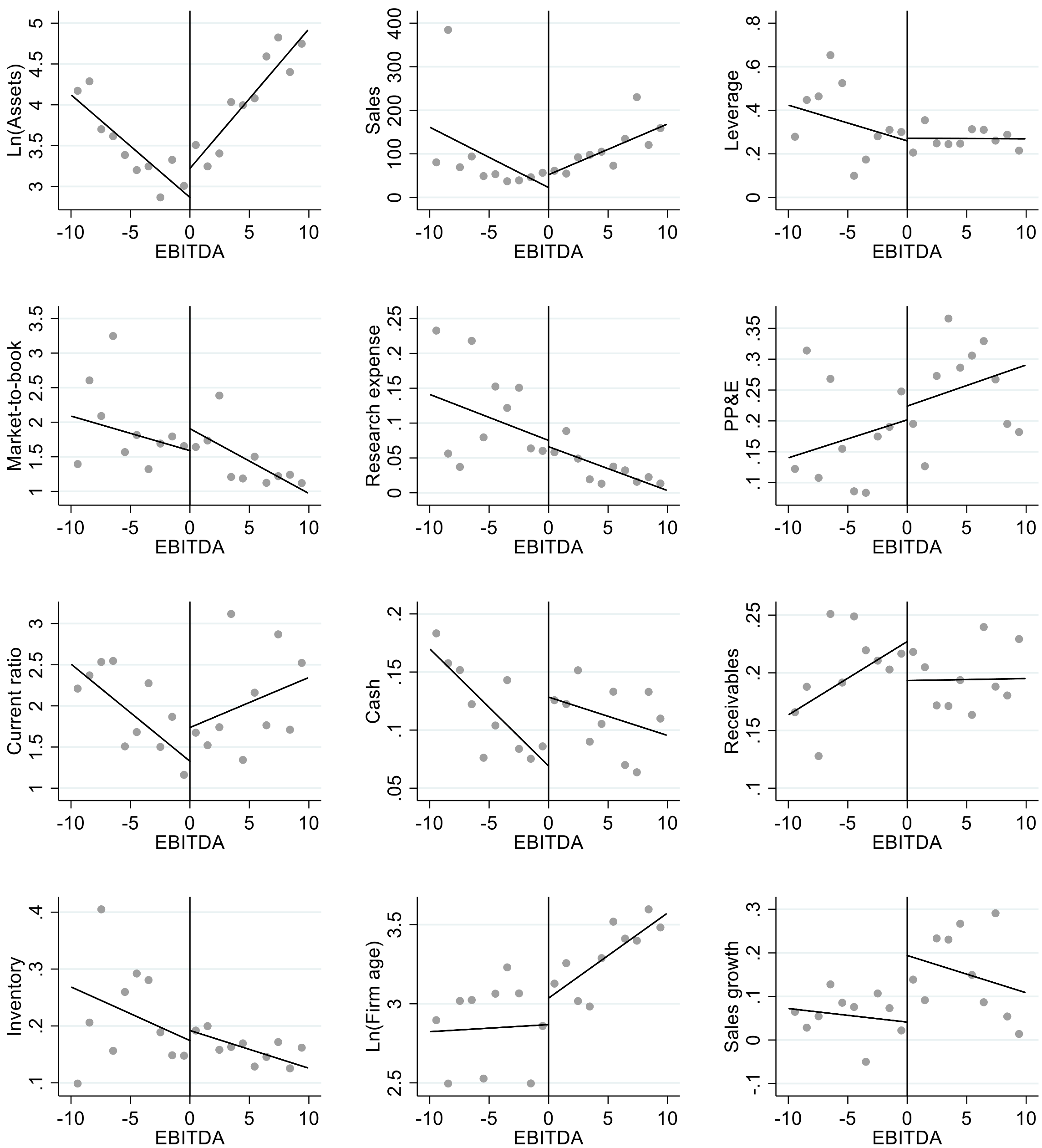

Figure A5: Behavior of covariates around the zero EBITDA boundary
This figure shows the behavior of various firm characteristics for borrowers whose trailing twelve month EBITDA is between minus $10 million and plus $10 million. Ten even spaced bins are created on either side of the boundary and means are reported for each bin.

Table A1: Cluster analysis solutions

For different values of *k*, this table shows the grouping of loans determined by *k*-medians clustering on deal size, maturity, whether or not the loan charges a fixed interest rate, the initial interest rate, whether or not the loan is senior, whether it is secured by a first lien, second lien, or unsecured, as well as the borrower's EBITDA, leverage, and total assets in 2015 US dollars. The table reports how many loans by each type of lender are grouped into each cluster. Panels A through C use the entire sample of loans issued by the 632 sample firms from 2010-2015. Panel D excludes bank loans.

Panel A: Four clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
BDC	4	1	0	6
Bank	282	231	87	21
Bank FCO	15	6	2	6
FCO	32	14	4	25
Hedge fund	8	3	2	39
Insurance	1	3	2	7
Investment bank	3	19	2	9
Investment manager	1	0	1	20
Other	1	1	0	3
PE/VC	14	0	3	32

Panel B: Five clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
BDC	0	4	3	0	4
Bank	228	22	280	87	4
Bank FCO	6	6	13	2	2
FCO	13	21	26	4	11
Hedge fund	3	20	6	1	22
Insurance	3	4	1	2	3
Investment bank	19	6	3	1	4
Investment manager	0	15	1	1	5
Other	1	3	1	0	0
PE/VC	0	15	7	1	26

Panel C: Six clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
BDC	4	0	0	3	4	0
Bank	4	201	82	209	21	104
Bank FCO	1	6	2	14	5	1
FCO	11	12	3	25	21	3
Hedge fund	22	4	1	5	20	0
Insurance	3	3	2	0	5	0
Investment bank	3	10	1	1	5	13
Investment manager	5	0	1	1	15	0
Other	0	1	0	1	3	0
PE/VC	26	0	1	7	15	0

Panel D: Four clusters, excluding banks

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
BDC	4	0	4	3
Bank FCO	4	5	19	1
FCO	20	11	33	11
Hedge fund	19	5	7	21

Insurance	4	4	2	3
Investment bank	3	18	8	4
Investment manager	15	0	2	5
Other	3	0	2	0
PE/VC	15	1	8	25

Table A2: Cluster summary statistics

For different values of *k*, this table shows the grouping of loans determined by *k*-medians clustering on deal size, maturity, whether or not the loan charges a fixed interest rate, the initial interest rate, whether or not the loan is senior, whether it is secured by a first lien, second lien, or unsecured, as well as the borrower's EBITDA, leverage, and total assets in 2015 US dollars. The table reports means of loan and firm characteristics for the observations in each cluster. Panels A through C use the entire sample of loans issued by the 632 sample firms from 2010-2015. Panel D excludes bank loans.

Panel A: Four clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Deal size	39.35	361.36	190.61	19.95
Maturity	3.36	4.97	4.24	3.77
Fixed rate loan	0.01	0.01	0.12	0.99
Interest rate	464.51	328.81	241.39	924.00
Performance pricing	0.21	0.40	0.46	0.00
Senior	0.88	0.98	0.95	0.68
Secured	1.00	1.00	0.00	0.80
Second lien	0.02	0.01	0.00	0.05
Financial covenants	0.80	0.95	0.81	0.30
Warrants	0.08	0.00	0.01	0.29
Convertible debt	0.01	0.01	0.04	0.20
Upfront fee	26.76	18.18	2.26	42.65
Annual fee	3.55	0.68	1.51	4.01
Total assets	175.55	977.00	892.72	161.97
EBITDA	8.26	129.89	125.20	4.32
Profitability	0.01	0.14	0.11	-0.16
PP&E	0.22	0.31	0.25	0.23
Leverage	0.24	0.37	0.22	0.39
Firm age	31.62	40.17	54.06	25.86
Volatility	0.67	0.47	0.41	0.80
Market-to-book	1.58	1.45	1.89	1.82
Research expense	0.07	0.02	0.04	0.10
Current ratio	2.32	2.38	2.95	1.80
Sales growth	0.13	0.12	0.07	0.11

Panel B: Five clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Deal size	365.42	22.17	40.80	195.12	25.79
Maturity	4.97	3.89	3.37	4.20	3.56
Fixed rate loan	0.01	0.99	0.01	0.10	0.69
Interest rate	327.20	858.77	430.39	237.83	986.97
Performance pricing	0.41	0.00	0.22	0.47	0.00
Senior	0.99	1.00	0.94	0.97	0.00
Secured	1.00	0.85	1.00	0.00	0.75
Second lien	0.01	0.05	0.00	0.00	0.11
Financial covenants	0.95	0.28	0.79	0.83	0.51
Warrants	0.00	0.27	0.06	0.01	0.28
Convertible debt	0.01	0.16	0.01	0.01	0.22
Upfront fee	18.40	38.27	25.95	2.36	46.07
Annual fee	0.58	5.03	3.60	1.57	1.98
Total assets	990.48	188.8	178.08	918.32	125.93
EBITDA	131.64	10.27	8.91	129.48	-3.39
Profitability	0.14	-0.14	0.02	0.13	-0.18
PP&E	0.31	0.25	0.22	0.26	0.20

Leverage	0.37	0.35	0.23	0.21	0.44
Firm age	40.48	24.88	31.08	55.57	30.37
Volatility	0.48	0.80	0.66	0.41	0.76
Market-to-book	1.46	1.80	1.59	1.85	1.77
Research expense	0.02	0.10	0.07	0.04	0.10
Current ratio	2.37	1.96	2.35	2.99	1.67
Sales growth	0.12	0.16	0.13	0.06	0.05

Panel C: Six clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Deal size	23.76	136.66	188.22	30.50	20.08	623.79
Maturity	3.53	4.96	4.28	2.85	3.92	5.01
Fixed rate loan	0.71	0.01	0.10	0.01	0.99	0.01
Interest rate	995.21	310.10	225.00	483.24	860.97	326.15
Performance pricing	0.00	0.40	0.49	0.15	0.00	0.46
Senior	0.00	0.97	0.97	0.94	1.00	0.99
Secured	0.75	1.00	0.00	0.99	0.85	0.97
Second lien	0.10	0.02	0.00	0.00	0.04	0.01
Financial covenants	0.49	0.91	0.84	0.76	0.29	0.96
Warrants	0.29	0.00	0.00	0.08	0.27	0.00
Convertible debt	0.23	0.01	0.01	0.01	0.16	0.00
Upfront fee	45.91	11.17	1.66	30.86	37.51	26.33
Annual fee	2.01	1.43	0.82	4.40	4.72	0.15
Total assets	122.44	458.50	744.59	154.60	179.07	1694.39
EBITDA	-3.12	58.89	102.38	3.13	7.31	229.86
Profitability	-0.18	0.13	0.14	-0.02	-0.15	0.15
PP&E	0.20	0.26	0.26	0.22	0.25	0.36
Leverage	0.45	0.25	0.20	0.25	0.35	0.46
Firm age	30.19	40.72	57.40	27.72	25.04	40.45
Volatility	0.76	0.50	0.39	0.72	0.81	0.47
Market-to-book	1.75	1.53	1.85	1.59	1.81	1.41
Research expense	0.10	0.03	0.03	0.08	0.10	0.01
Current ratio	1.62	2.56	3.01	2.18	1.98	2.37
Sales growth	0.04	0.12	0.07	0.13	0.16	0.12

Panel D: Four clusters, excluding banks

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Deal size	17.79	297.27	59.91	22.15
Maturity	3.6	5.47	3.88	3.6
Fixed rate loan	1	0.27	0.02	0.77
Interest rate	915.29	621.14	610.25	1011.19
Performance pricing	0	0.14	0.1	0
Senior	1	0.93	0.84	0
Secured	0.82	0.89	0.92	0.71
Second lien	0.03	0.1	0.03	0.08
Financial covenants	0.21	0.82	0.71	0.44
Warrants	0.33	0.02	0.16	0.3
Convertible debt	0.21	0.02	0.04	0.26
Upfront fee	32.74	71.83	31.07	47.34
Annual fee	6.21	1	4.53	2.08
Total assets	127.52	1267.25	211.44	119.32
EBITDA	-3.50	137.05	6.65	-3.49
Profitability	-0.20	0.13	-0.06	-0.18
Tangibility	0.23	0.36	0.23	0.20
Leverage	0.35	0.51	0.32	0.44

Firm age	21.24	46.34	31.54	28.16
Volatility	0.82	0.60	0.66	0.76
Market-to-book	1.95	1.13	1.56	1.80
Research expense	0.12	0.02	0.07	0.09
Current ratio	1.94	2.06	2.07	1.64
Sales growth	0.20	0.09	0.06	0.06

Table A3: OLS regressions for similarities and differences across loans made by different types of lenders

The dependent variable is stated in the table as "Type A vs. Type B". If the loan is made by lender type A, the dependent variable equals one, and if it is made by type B, the dependent variable equals zero. Loans made by other lender types are excluded. Independent variables are standardized to have mean zero and a standard deviation of one. Observations are aggregated to the deal level. Standard errors are clustered at the firm level. FCO denotes finance companies. HF denotes hedge funds. BDC denotes business development companies. IM denotes investment managers. PE/VC denotes private equity firms and venture capital firms. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Bank FCO vs. Bank	Bank FCO vs. FCO	HF vs. BDC/ PE/VC/IM	IM vs. BDC/HF/ PE/VC	PE/VC vs. BDC/HF/IM	BDC vs. HF/IM/ PE/VC	BDC/PE/VC vs. HF/IM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(Deal size)	-0.0323	-0.0205	0.1072	-0.0573	-0.0587	0.0087	-0.0500
	(-1.61)	(-0.17)	(1.20)	(-0.93)	(-0.66)	(0.23)	(-0.59)
Maturity	0.0016	-0.0423	0.0387	0.0272	-0.0718	0.0060	-0.0659
	(0.17)	(-0.63)	(0.44)	(0.47)	(-0.80)	(0.25)	(-0.74)
Fixed rate loan	0.0560*	0.0328	0.0504	0.0089	-0.0385	-0.0207	-0.0592
	(1.68)	(0.74)	(0.94)	(0.27)	(-0.70)	(-0.76)	(-1.15)
Initial interest rate	-0.0170	-0.3031***	0.0090	-0.0515	0.0432	-0.0008	0.0425
	(-0.73)	(-5.85)	(0.13)	(-1.32)	(0.73)	(-0.04)	(0.74)
Senior	-0.0814**	-0.0482	0.0039	0.0731***	-0.0584	-0.0185	-0.0769**
	(-2.34)	(-1.13)	(0.09)	(2.81)	(-1.58)	(-1.04)	(-2.11)
Second lien	0.0103	0.0204	0.0050	-0.0073	0.0277	-0.0254*	0.0023
	(0.39)	(0.85)	(0.17)	(-0.46)	(1.20)	(-1.83)	(0.10)
Secured	0.0055	0.0088	0.0160	-0.0977**	0.0536	0.0280	0.0816**
	(0.70)	(0.13)	(0.36)	(-2.31)	(1.44)	(1.64)	(2.25)
EBITDA	-0.0097	0.1009	0.0620	-0.2560***	0.2106	-0.0166	0.1940
	(-1.52)	(0.57)	(0.32)	(-3.48)	(1.12)	(-0.27)	(0.95)
Leverage	0.0239*	0.0242	0.0738*	0.0198	-0.0934**	-0.0002	-0.0936**
	(1.86)	(0.50)	(1.92)	(0.65)	(-2.62)	(-0.01)	(-2.64)
Ln(Assets)	0.0206	-0.1132	-0.0486	0.0382	0.0113	-0.0009	0.0104
	(0.96)	(-0.98)	(-0.56)	(0.54)	(0.15)	(-0.03)	(0.14)
Research expense	-0.0233**	-0.0242	-0.0522	-0.0500**	0.0364	0.0658**	0.1022***
	(-2.28)	(-0.81)	(-1.51)	(-2.25)	(1.01)	(2.33)	(2.98)
Growth	-0.0078	-0.0310	-0.0720**	-0.0265	0.0610	0.0375*	0.0985***
	(-0.87)	(-0.74)	(-2.03)	(-0.98)	(1.48)	(1.68)	(2.72)
Constant	0.0830***	0.4490***	0.4043**	0.2123*	0.2634	0.1199	0.3834**
	(2.99)	(3.66)	(2.32)	(1.73)	(1.63)	(1.45)	(2.46)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	628	97	124	124	124	124	124

Table A4: Testing for a discontinuity in the probability of borrowing from a nonbank

This table uses local linear polynomials in EBITDA to test whether there is a discontinuity in the probability of borrowing from a nonbank around zero EBITDA (Gelman and Imbens 2014). EBITDA is calculated on the trailing twelve months basis at loan origination. Going from left to right, the columns zoom in on neighborhoods around zero EBITDA, starting with a range of plus/minus $100 million and ending with a range of plus/minus $5 million dollars. The sample includes all borrowings of a random sample of 632 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level. *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

EBITDA range	[-100,100] (1)	[-50,50] (2)	[-25,25] (3)	[-10,10] (4)	[-5,5] (5)
EBITDA < 0	0.33***	0.36***	0.41***	0.47***	0.45***
	(5.24)	(5.03)	(5.34)	(4.99)	(3.88)
EBITDA	-0.00**	-0.00	0.01**	0.02	0.01
	(-2.59)	(-0.82)	(1.97)	(1.09)	(0.37)
(EBITDA < 0)	0.00	0.00	-0.01	-0.01	-0.01
x EBITDA	(0.06)	(0.56)	(-1.34)	(-0.78)	(-0.15)
Constant	0.28***	0.27***	0.20***	0.17***	0.19**
	(7.78)	(6.60)	(4.41)	(2.71)	(2.41)
Observations	801	665	503	338	212

Table A5: Testing for discontinuities in the covariates

This table uses local linear polynomials in EBITDA to test whether there is a discontinuity in the regression covariates around zero EBITDA. For each covariate, two regressions are reported. The first regression restricts the sample to observations with an EBITDA within the range of plus/minus \$10 million, and the second restricts the range to plus/minus \$5 million. *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	EBITDA ∈ [-10,10]				EBITDA ∈ [-5,5]			
	EBITDA < 0	EBITDA	(EBITDA < 0) x EBITDA	Constant	EBITDA < 0	EBITDA	(EBITDA < 0) x EBITDA	Constant
Ln(Assets)	-0.35	0.17***	-0.30***	3.22***	-0.18	0.15**	-0.17	3.25***
	(-1.41)	6.05	(-5.56)	(20.47)	(-0.54)	(2.14)	(-1.56)	(15.37)
Sales	-29.44	11.64***	-25.52***	52.11***	-0.46	11.08	-8.56	53.81***
	(-1.18)	4.60	(-2.94)	(4.01)	(-0.01)	(1.33)	(-1.23)	(2.92)
Leverage	-0.01	-0.00	-0.02	0.27***	0.05	-0.01	0.06**	0.29***
	(-0.18)	(-0.03)	(-1.22)	(5.45)	(0.62)	(-0.71)	(2.17)	(4.54)
Market-to-book	-0.32	-0.09**	0.04	1.91***	-0.46	-0.16**	0.12	2.05***
	(-0.82)	(-2.39)	(0.66)	(6.39)	(-1.05)	(-2.10)	(0.76)	(6.42)
Research expense	0.01	-0.01***	-0.00	0.07***	-0.03	-0.01**	-0.01	0.08***
	(0.31)	(-2.75)	(-0.05)	(3.57)	(-1.03)	(-2.52)	(-0.83)	(3.58)
PP&E	-0.02	0.01	-0.00	0.22***	0.12	0.04**	0.00	0.15***
	(-0.42)	(1.17)	(-0.04)	(6.13)	(1.57)	(2.15)	(0.16)	(3.39)
Current ratio	-0.41	0.06	-0.18**	1.74***	-0.30	0.15	-0.31**	1.56***
	(-1.26)	(1.04)	(-2.07)	(7.22)	(-0.86)	(1.44)	(-2.40)	(6.04)
Cash	-0.06**	-0.00	-0.01	0.13***	-0.06**	-0.01	-0.00	0.14***
	(-2.57)	(-1.02)	(-1.15)	(7.38)	(-2.52)	(-0.91)	(-0.45)	(6.83)
Receivables	0.03	-0.00	0.01	0.19***	0.00	-0.01	0.01	0.21***
	(1.08)	(0.04)	0.93	(7.76)	(-0.03)	(-0.81)	(0.28)	(7.02)
Inventory	-0.02	-0.01	-0.00	0.19***	-0.08	-0.01	-0.03	0.20***
	(-0.34)	(-1.09)	(-0.30)	(5.29)	(-1.23)	(-0.46)	(-1.43)	(4.52)
Ln(Firm age)	-0.17	0.05**	-0.05	3.04***	-0.38	-0.00	-0.07	3.14***
	(-0.84)	(2.34)	(-1.26)	(24.10)	(-1.54)	(-0.03)	(-0.67)	(19.73)
Sales growth	-0.15*	-0.01	0.01	0.19***	-0.08	0.04	-0.05	0.10
	(-1.71)	(-0.92)	(0.31)	(3.37)	(-0.65)	(1.20)	(-0.96)	(1.32)

Table A6: Fuzzy regression discontinuity design using ad hoc neighborhood selection

The table reports the results of fuzzy RDD estimation using local linear polynomials. The outcome variable is the initial interest rate. The treatment is borrowing from a nonbank. The running variable is trailing twelve-month EBITDA, with a discontinuity at zero. The slope of the effect of the running variable on the probability of treatment is allowed to differ to the left and right of the discontinuity. Two-stage least squares estimation is employed to estimate the treatment effect. *t*-statistics that adjust for clustering at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

Panel A: First stage of IV

EBITDA range	[-100,100]	[-50,50]	[-25,25]	[-10,10]	[-5,5]
	(1)	(2)	(3)	(4)	(5)
Negative EBITDA	0.36***	0.40***	0.41***	0.42***	0.41***
	(6.31)	(5.81)	(5.06)	(4.31)	(2.88)
EBITDA	-0.00**	-0.00	0.01	-0.00	0.02
	(-2.29)	(-1.10)	(1.25)	(-0.13)	(0.53)
Negative EBITDA x EBITDA	0.00	0.00	-0.01	0.01	-0.02
	(0.58)	(0.89)	(-1.04)	(0.40)	(-0.38)
Ln(Assets)	0.02	0.02	-0.00	0.03	0.02
	(0.78)	(0.97)	(-0.07)	(1.09)	(0.63)
Leverage	0.44***	0.48***	0.52***	0.57***	0.58***
	(5.80)	(6.12)	(6.12)	(5.61)	(4.54)
Research expense	-0.05	-0.13	0.09	0.14	0.28
	(-0.27)	(-0.74)	(0.51)	(0.74)	(0.90)
PP&E	-0.05	-0.04	-0.15	-0.20	-0.18
	(-0.41)	(-0.26)	(-0.86)	(-1.12)	(-0.77)
Cash	-0.18	-0.26	-0.40**	-0.40*	-0.58*
	(-1.10)	(-1.39)	(-1.99)	(-1.78)	(-1.82)
Receivables	0.04	-0.04	-0.10	0.04	0.23
	(0.20)	(-0.19)	(-0.45)	(0.19)	(0.69)
Inventory	-0.39***	-0.45***	-0.51***	-0.28	0.06
	(-2.98)	(-3.09)	(-2.85)	(-1.44)	(0.23)
Ln(Firm age)	0.01	0.03	0.04	0.01	-0.06
	(0.33)	(1.04)	(1.33)	(0.20)	(-1.46)
Constant	0.10	0.06	0.05	0.04	0.17
	(0.70)	(0.41)	(0.30)	(0.23)	(0.64)
Year effects	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes
Observations	734	603	453	299	189

Second stage IV (Dependent variable = Interest rate)

EBITDA range	[-100,100]	[-50,50]	[-25,25]	[-10,10]	[-5,5]
	(1)	(2)	(3)	(4)	(5)
Nonbank	578.67***	525.70***	480.60***	480.73***	388.22**
	(6.12)	(5.49)	(4.25)	(3.54)	(2.04)
EBITDA	-0.69	-1.12	-2.50	-6.53	-15.07
	(-1.13)	(-0.91)	(-0.93)	(-0.87)	(-1.08)
Negative EBITDA x EBITDA	-2.75	-3.38	-2.71	5.45	1.44
	(-1.60)	(-1.33)	(-0.51)	(0.52)	(0.05)
Ln(Assets)	-42.66***	-43.21***	-46.05***	-45.73***	-28.10
	(-3.64)	(-3.43)	(-3.08)	(-2.79)	(-1.34)
Leverage	62.71	71.64	44.81	-57.43	-159.03
	(0.92)	(0.97)	(0.50)	(-0.58)	(-1.15)
Research expense	-25.42	-28.43	-61.13	8.57	5.19
	(-0.27)	(-0.26)	(-0.50)	(0.06)	(0.03)
PP&E	-30.83	-11.26	20.78	175.28	219.62*
	(-0.39)	(-0.13)	(0.19)	(1.62)	(1.69)
Cash	-18.35	-0.39	-55.33	-66.37	-230.55
	(-0.18)	(-0.00)	(-0.41)	(-0.45)	(-0.99)
Receivables	-175.84	-131.13	-160.76	-135.15	-284.80
	(-1.50)	(-1.05)	(-1.18)	(-0.86)	(-1.42)
Inventory	22.45	30.32	36.39	76.74	-57.34
	(0.24)	(0.29)	(0.30)	(0.64)	(-0.38)
Ln(Firm age)	-16.94	-17.48	-23.32	-6.52	18.33
	(-1.15)	(-1.06)	(-1.20)	(-0.32)	(0.64)
Constant	666.43***	670.95***	763.90***	674.93***	657.01***
	(6.51)	(6.21)	(6.22)	(4.83)	(3.49)
Year effects	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes
Observations	734	603	453	299	189