Nonbank Lending

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ABSTRACT

We provide the first 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 lending from nonbank financial institutions is substantial, with 30% of all loans being extended by nonbanks. Firms that borrow from nonbank lenders are smaller, riskier, and significantly more likely to have negative EBITDA. Nonbank lenders are less likely to include financial covenants in their loans, but appear to engage in substantial ex-ante screening: origination of nonbank loans is associated with larger positive announcement returns and ex-post performance is not distinguishable from bank loans. We also find that nonbank borrowers pay about 200 basis points higher interest rates on average than bank borrowers do. 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 (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 very little systematic evidence on the direct lending by nonbank lenders to such businesses. This lack of systematic evidence stems both from limited data availability and also from the commonly-held view in the literature on debt financing that firms choose between private debt financing provided or arranged by banks and arm's length public bond financing provided by capital markets. This paper presents novel evidence on the sources and terms of debt financing and challenges the traditional narrative that banks are special in being the only type of financial intermediaries that engage in commercial and industrial lending that involves screening and monitoring borrowers (Fama 1985, James 1987).

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) as well as to the syndicated loan market, middle market firms are more likely to be affected by the availability of bank and other forms of sole-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 exact price and non-price terms offered by different types of lenders.

[1] See, for example, Ahmed (2011), Griffiths (2011), and Carley (2010). One example of a mid-size firm borrowing from hedge funds is Rentech, a Los Angeles based firm focused on developing clean energy solutions. Unable to borrow from its relationship banks, Rentech turned to Highbridge Capital Management, other hedge funds, and then GE Capital, a finance company, for funding during and after the crisis.

[2] National Center for the Middle Market info sheet
http://www.middlemarketcenter.org/Media/Documents/NCMM_InfoSheet_2017_web_updated.pdf

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 substantial: About one third of all commercial and industrial loans taken out by publicly-traded middle market firms are 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 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 documenting the extent of nonbank lending, we explore the characteristics of firms that borrow from nonbank lenders and differences in the terms of lending between bank and nonbank lenders. Firms that borrow from nonbank lenders are smaller and younger, spend more on R&D, and are more likely to have negative EBITDA than firms that borrow from banks. 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 35% more likely to borrow from a nonbank lender than are firms with small positive EBITDA.

This 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 around 500 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). Along with charging higher interest rates, nonbank lenders charge 86 basis points higher upfront fees and 21 basis points higher annual fees.

According to our RDD analysis, nonbank loans are 58% 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, nonbank lenders impose discipline through 2.65 years shorter maturities and by including warrants to better align incentives.

Nonbank lenders also appear to engage in significant ex-ante screening. We find abnormal announcement returns around origination of nonbank loans of 1.6-3.2%. These returns are statistically significantly different not only from zero but also from the announcement returns for bank loans of 0.1-0.9%. 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 rely more on ex-ante screening and alignment of incentives.

Our final set of analyses looks at 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.

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 completely bypassing banks and lending directly to firms. 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, non-bank 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 covers larger firms and allows us to study the characteristics of firms that borrow from different types of lenders as well as the price and non-price contact terms. 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) is the only paper that we are aware of that looks at hedge funds as primary lenders. These authors 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 lenders type 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 between bank and nonbank loans in terms of both pricing and nonpricing terms. 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. Section 6 concludes.

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 the loans they extend to providers of standard databases such as DealScan or Leveraged Commentary and Data (LCD). As a result, our nonbank loan data are largely hand collected. We complement this nonbank lending data set with hand collected sole-lender bank loans as well as with syndicated loans supplemented from DealScan.

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

Our sample consists of a set of 750 publicly traded middle market firms taken from the domestic population of Compustat that are active between 2010 and 2015.[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 capture unprofitable firms. 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 have book leverage of at least five percent at some point during the 2010-2015 period. Financial firms and utilities are excluded.

The domestic population of Compustat contains a nontrivial number of firms that are de facto foreign, such as firms whose headquarters and productive assets are located in China but whose primary exchange listing is in the US. We wish to exclude such firms to ensure that all debt in our sample is backed primarily by US assets and thus subject to the same legal and institutional environment. To this end, we obtain the location of the firm's headquarters as well as its incorporation and exclude foreign firms indicated by either of these two locations. This step leaves us with 632 firms.

Regulation S-K requires material contracts such as debt contracts to be filed as exhibits to SEC filings. Capital IQ provides links to these exhibits for every registered firm it covers. Because coverage in Capital IQ has improved over time, we focus on a recent sample of contracts filed between 2010 and 2015. As discussed in Appendix A, cross-referencing with DealScan suggests that coverage is fairly comprehensive during the sample period. For each firm we obtain links to all credit documents in the SEC's EDGAR database and download these filings. We exclude bonds, but retain any other debt contracts such as lines of credit, term loans, and promissory notes. Debt contracts are frequently renegotiated. To avoid capturing minor renegotiations and maturity extensions, we restrict our sample to original contracts as well as amended and restated agreements. We exclude simple amendments, covenant waivers, joinder agreements, and documents that refer to an existing credit agreement.

[4] More detailed discussion of sample construction and data extraction can be found in Appendix A.
[5] http://www.middlemarketcenter.org

To economize on manual data collection, we attempt to match all contracts to DealScan based on 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 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 characteristics such as the tranche structure, amount, maturity, interest rate, fees, priority, presence of financial covenants or warrants, etc.

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 loan's origination date plus the stated spread. If the contract stipulates an interest rate floor, we use the greater of the calculated interest rate and the floor.

To understand what type of firm borrows from what type of nonbank lender 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). Most banks have the word "bank" in their name. We search for the remaining lenders in Capital IQ and read their business descriptions. If the lender is an individual, a nonfinancial corporation[7] or a government entity, we exclude the contract from the sample. Syndicated loans are classified according to the identity of the lead arranger.

Borrower financials are taken from Compustat. Capital IQ data are used to supplement financials whenever unavailable in Compustat. 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

[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.

expense to assets as well as sales growth and the change in the ratio of EBITDA to assets at a value of one. The final example consists of 1,047 debt contracts entered into by 471 borrowers.

2.2 Summary statistics

Panel A of Table 1 shows how many bank and nonbank loans are originated for our sample firms in our sample period of 2010-2015. Observations are reported at the deal level, rather than at the tranche level as there are typically a few tranches in syndicated loans. About 30% of sample loans are extended by nonbank lenders. Panel B shows different types of nonbank lenders that form this 30% on average. These lenders are 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 (26.2%), PE/VC firms (18.3%), and hedge funds (17.4%) hold largest fraction of nonbank lending in our sample. Table 1 also shows that only 20% of nonbank loans are tracked in DealScan. In particular, DealScan rarely covers loans extended by asset managers.

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.

Nonbank borrowers are significantly smaller than bank borrowers in terms of their book assets and EBITDA. The average nonbank borrower has book assets of $295 million and EBITDA of $18 million. The average bank borrower has book assets of $571 million and EBITDA of $69 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

[8] Others include collateralized loan obligations, mutual funds and real estate investment trusts.

nonbanks. The fraction of loans extended by nonbanks drops sharply from around 60% to the left of zero EBITDA to around 25% to the right of zero EBITDA. We will use this jump later on in our fuzzy regression discontinuity analyses.

Compared to bank borrowers, firms that borrow from nonbanks are younger (28.8 vs. 38.1 years), spend a larger fraction of their assets on R&D (9.1% vs. 3.7%), and have higher market-to-book ratios (1.79 versus 1.54). Nonbank borrowers also appear to experience greater stock return volatility.

Along with being smaller, nonbank borrowers get smaller loans ($73 vs. $185 million), but report higher leverage prior to loan origination (36% 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 warrants and convertible debt.

We next turn to multivariate regression analysis of the characteristics of bank and nonbank borrowers. Table 3 reports the marginal effects from Probit regressions of whether a loan is extended by a nonbank lender. While the effect of firm size is negative, it is not statistically significant. EBITDA appears to be a more important determinant of whether a firm borrows from a bank or nonbank lender. When we add a dummy for negative EBITDA in column 2, the effect of raw EBITDA is significantly reduced. Consistent with the results in Figure 1, the effect of EBITDA seems to be driven in large part by whether a firm has positive EBITDA or not.

Leverage and R&D intensity are associated with a significantly higher probability of borrowing from a nonbank lender. In column 4, 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, suggesting that firms with significant inventories that could be used as collateral are more likely to borrow from banks.

Finally, column 5 adds borrower fixed effects. Since we do not have as much within borrower as cross borrower variation, most of the coefficients are no longer statistically significant, though they retain their magnitudes. The effect of negative EBITDA retains its

statistical significance and is even larger in magnitude. These results once again point to the importance of positive EBITDA in affecting the choice of lender type.

So far we have been treating 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 three outcomes are 1) borrowing from an independent finance company or a bank-affiliated financed company, 2) borrowing from an investment bank, and 3) 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. We drop loans made by insurance companies from our detailed analyses due to a paucity of observations. Compared with bank borrowers, firms borrowing from FCOs and asset managers are smaller and are more likely to have negative EBITDA and higher leverage. However, borrowers from investment banks differ in that they are on average larger than bank borrowers. They are also similar to bank borrowers in their leverage and likelihood of having a positive EBITDA.

Model 2 separates bank FCOs and unaffiliated FCOs, and Model 3 separates hedge funds and investment managers from other types of asset managers.[9] Bank FCOs and unaffiliated FCOs are similar in their lending preferences, with one exception. Bank FCOs have a stronger preference to lend to firms that have collateral in the form of property, plant & equipment (Wald test *p*-value for difference in relative risk ratios: 0.024) or accounts receivable (*p*-value: 0.067).

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

[9] 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.

business development companies, private equity, or venture capital (*p*-value for difference in relative risk ratios: 0.030). The latter group is more likely to lend to firms that hold little inventory (*p*-value: 0.064) and engage in a lot of R&D (*p*-value: 0.013). 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.

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 characteristics of firms that borrow from bank versus nonbank lenders. In particular, as we just saw, firms that borrow from nonbanks are smaller and 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, if 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 spread charged on the loan 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, EBITDA less than zero, 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 changed on nonbank versus bank loans. The difference of 484 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 394 basis points. The coefficients on firm characteristics are consistent with theory. Larger firms and the ones that have more tangible assets, either in terms of PP&E or receivables and inventories, pay significantly lower interest rates. A doubling in firm size is associated with 41 basis points

lower interest rate. A ten percentage points increase in PP&E, receivables, or inventories is associated with 15-25 basis points lower interest rate. Unprofitable firms pay 148 basis points more.

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 394 basis points to 229 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 that command 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 60 to 35 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 7-8 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.

Column 5 controls for the volatility of borrowers' stock returns.[10] Besides reducing the coefficient on the nonbank dummy from 231 to 196 basis points, the main effect of controlling for volatility is to reduce the magnitude of the coefficients on warrants and convertible debt, indicating that these are more likely to be included in loans extended to riskier firms.

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. Independent finance companies and investment banks charge about 210-250 basis points higher interest rates, while various types of asset managers charge about 430-475 basis points higher interest rates. Finally, in column 8 we

[10] To ensure that volatility is unaffected by the loan contract negotiation process, we measure volatility over calendar days -485 through -120 before loan origination.

include borrower fixed effects to control for time-invariant unobserved heterogeneity. The difference in interest rates between bank loans and nonbank loans increases to 300 basis points.

We also explore whether simultaneous equity ownership could explain the differences in interest rates charged (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 see that significant equity ownership in borrowing firms by our nonbank lenders is rare. Specifically, in only 5.79% of the nonbank loans, is the lender a blockholder with 5% or larger share. 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 and probit 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 profitability are important determinants of differences in loan size. Controlling for these, we find that finance companies and asset managers extend loans that are about 30-40% smaller[11] than bank loans.

In columns 3 and 4 the dependent variable is maturity. Loans by asset managers have 0.5-1 year shorter maturity, but this is entirely due to asset managers lending to small, unprofitable firms. The coefficient on negative EBITDA is particular large in magnitude and indicates almost

[11] For example, a coefficient on the log of loan amount of -0.5 corresponds to a 39% reduction.

1 year shorter 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 9-16% less likely to be senior after controlling for firm characteristics. In column 7, there is little difference in collateral requirements across lenders. However, column 8 shows that conditional on their propensity to lend to firms with low EBITDA for which lenders are more likely to require collateral, asset managers are particularly likely to make unsecured loans.

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. All 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 25-35% 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. 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 covenants, asset managers may engage in more ex-ante screening to identify creditworthy but risky borrowers. Announcement return evidence in Section 5.2 is consistent with this idea.[12]

Panel B also shows that FCOs and asset managers are much less likely than banks to use performance pricing in their loans. The coefficient for the PE/VC/BDC indicator cannot be estimated because the sample does not contain any loan with performance pricing made by these lenders. All nonbanks 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

[12] One may wonder whether nonbank lenders use less conventional monitoring tools. In particular, contracts sometimes assign inspection rights allowing the lender to inspect the borrower at the borrowers' expense or observer rights allowing the lender to attend board meetings as a non-voting member. We find that 1.15% of nonbank loans have observer rights compared to 0.29% of bank loans. While this difference is statistically significant, the absolute frequency of observer rights usage is very small. We also find that nonbanks are significantly less likely to obtain inspection rights than banks (3.7% vs. 17.4% of loans). These results underscore that on average nonbanks monitor borrowers less actively than banks.

strongly driven by the types of firms nonbanks lend to. Adding firm characteristics reduces the size of most coefficients by more than half 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. Nonbank loans are significantly more likely than bank loans to be fixed rate. This is consistent with banks relying on floating-rate funding and matching the interest rate exposure of their assets and liabilities (Kirti ,2017). Other than larger firms being less likely to borrow at fixed rates, none of the other firm characteristics are associated with the fixed versus floating choice.

Turning to upfront fees in columns 3 and 4, finance companies and investment banks charge 29 and 67 basis points higher upfront fees. About half of the effect for finance companies is explained by the characteristics of firms they lend to; controlling for these, size and negative EBITDA in particular, reduces the coefficient on finance company dummy from 29 to 16 basis points and makes it statistically not significantly different from zero. 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. 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, nonbanks are between 1.5% and 2.2% more likely than banks to make loans secured by a second lien. This difference is large considering that only 1.8% of sample loans are second lien loans.

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 ability 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 25-37% 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. 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 $5 million. While the mode of EBITDA is just above zero, the distribution appears smooth. If anything, the frequency of EBITDA just below zero is larger than the average of the frequencies of the two adjacent bars, which is inconsistent with borrowers being able to manipulate their EBITDA to just above zero. In the Internet Appendix, we zoom in to a smaller neighborhood around zero EBITDA and continue to find a smooth distribution.

Having shown that zero EBITDA allows us to utilize a fuzzy regression discontinuity design, we now present the results on the causal effect of borrowing from a nonbank lender on the 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 for each outcome variable 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. Internet appendix Table A5 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 [-43.17, 43.17]. In the second stage, we find an interest rate differential of 6.06% with a *z* statistic of -5.27. The reason this difference is larger than the coefficient on the nonbank lender dummy in Table 5 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.

In addition to carrying higher interest rates, nonbank loans pay 86 basis points higher upfront fees and 21 basis points higher annual fees. While there are no statistically differences in the loan amount, seniority, or security, nonbank loans have 2.65 years shorter maturity. Nonbank loans are 58 percentage points less likely to include financial covenants but 32 percentage points more likely to include warrants.

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 borrowing firm EBITDA.

Imbens and Rubin (2015) suggest using mean differences normalized by the standard deviation and the variance ratios to examine covariate balance even though the distribution of these statistics are not known and, therefore, exact cutoff points for any statistical tests cannot be obtained. 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 loan size. 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 and profitability. After matching, the balance improves with the difference of means approaching to 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 and profitability. The matched sample, however, is much better balanced with the variance ratio dropping to 1.1 for both firm size and profitability. Also, the variance ratio for EBITDA gets closer to 1, increasing specifically from

0.195 to 0.695. 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 loan size is negative and marginally significant at the 10% level, as presented in Column 1. For the initial interest rate on the loan, though, the estimated effect is positive with a coefficient of 414 basis points, statistically significant at the 1% level. These results provide strong evidence that nonbank lenders charge significantly higher interest rates on loans to similar borrowers in terms of firm size and profitability.

5 Ex-post performance of bank versus nonbank loans

Our evidence so far shows that compared to banks, nonbank lenders lend to smaller, less profitable, and riskier borrowers. To compensate for the greater risks involved, nonbank lenders also charge higher interest rates, though our analysis in Table 5 and Table 7 in particular indicates that a large part of the difference in interest rates cannot be explained by differences in risk. Next we analyze whether these loans end up being profitable for nonbank lenders. This analysis will also clarify why nonbank institutions make these loans, whether it financially makes sense for them to fill a gap in the market of riskier, smaller loans that banks exclude.

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 43 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 the marginal effects from Probit regressions predicting bankruptcy over the three years following loan origination. Numbers in parentheses are *z*-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 3.3% increase in the probability of bankruptcy. As we add firm characteristics such as size and dummy for negative EBITDA, the effect of nonbank lender drops to around 1.1-1.7% and is no longer statistically significant. Therefore, the evidence on non-bank 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. It is worth to note, however, that the loss in significance on the coefficient is mostly due to some IPO firms being dropped from the sample. Profitability prior to loan origination is on average very high for these IPO firms and it declines immediately after the IPO, driving the significance in the coefficient when these IPO borrowers are included in the sample. 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, investment bank, and hedge fund/investment manager dummies in the first specification to

nonbank lender dummy as in Panel A. The coefficients range from about -4% for investment banks to -7.7% for hedge funds/investment managers. Again, we see almost no significance in coefficients (except for a negative coefficient for PE/VC/BDC in Column 3 or positive one for FCO dummy in Column 6, both significant only at the 10% level) for the second and third years.

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 non-bank lender dummy or various types of nonbank-lender dummies except for the PE/VC/BDC dummy having a negative and significant coefficient.

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 1.7% implies a 1.7% 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 less than 0.3% 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

In this section, we study whether announcements of nonbank loans are assessed by the market as valuable or comparable to bank loans. We do so by calculating cumulative announcement returns (CARs) around origination of loans by bank versus nonbank lenders. We know from prior literature that announcement returns to bank loans are positive on average.[13]

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 seven calendar days of loan origination. Results are presented in Table 11 and show that CARS for nonbank loans are larger than CARs for banks. For all loans, as presented in Row 1, mean (median) abnormal return is 2.05% (1.36%) for nonbank loans,

[13] See for example, James (1987), Lummer and McConnell (1989), and many other afterwards.

while it is 0.78% (0.17%) for bank loans. Differences remain when we concentrate on stocks with a stock price larger than $5.

6 Conclusion

We present the first systematic evidence on direct lending by nonbank financial intermediaries to publicly traded middle market firms. Such lending is widespread with about one third of all loans in our data being extended by nonbanks. Smaller, unprofitable firms are significantly more likely to turn to nonbank intermediaries for loans. 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 500 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 Compustat that meet the following criteria:

- The firm is active at some point between 2010-2015
- Revenues are between $10 million and $1 billion
- Compustat contains data on common shares outstanding and stock price
- CIK is not missing
- The ratio of long-term debt and debt in current liabilities to total assets is larger than 0.05
- The firm's SIC code is not between 6000 and 6999 (financials) or between 4900 and 4999 (utilities)
- The filing currency is US dollars
- The filing is not a red herring ("-REDH" in company name), pro-forma ("PROFORMA" in company name), pre-amended ("PREAMEND in company name) or ADR ("ADR" in company name or Compustat data item ADRR is nonmissing)
- Exchange code is not 0 (subsidiary/private), 1 (non-traded company or security), or 4 (additional company record such as pre SFAS 94, pro-forma or pre-amended records)

We obtain historical data on headquarters location and country of incorporation from the company header history in CRSP/Compustat Merged. We examine firms that have either their headquarters or their incorporation outside of the US. Such firms tend to be primarily Chinese firms whose primary stock market listing is in the US, Canadian firms that provide a filing in US dollars, and firms located and/or incorporated in an offshore financial center. A handful of firms are incorporated and located in Israel or Ireland. We exclude all of these firms. This restriction leaves 632 firms in the sample. Among these, 23 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 document name and type as well as a link to the SEC filing in EDGAR. The following document types contain the body of actual debt contracts and are retained:

- Credit Agreement
- Debt & Loan Agreement
- Notes Agreement
- Securities Purchase Agreement

Other document types either relate to types of debt we do not wish to examine (e.g., Underwriting Agreements and Indentures) or to supplemental filings (e.g. Rights Agreements, Guarantee Agreement, Indemnity Agreement, etc.). These are excluded.

Notes Agreements can relate to promissory notes or to bonds. 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. This filter eliminates most bonds, but also eliminates large syndicated deals. We obtain the latter from DealScan as described further

below. Promissory notes can either be standalone notes or they can be notes issued pursuant to an existing credit agreement. We drop the latter and refer only to the original credit agreement.

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.

In addition, we drop loan modifications, forbearances, covenant waivers, confirmations, acknowledgments, assignments, exchanges, joinder agreements, documents relating to repayments, terminations, participation letters, post-closing letters and other supplemental documents as well as any duplicate filings. We also drop a small number of debt contracts that are filed in 2010-2015, but have an origination date prior to 2010.

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 have an amount of less than $250 million and 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. In one case, the firm mentions the credit agreement in the 10-K, but does not file it. In that particular case, almost all variable fields in DealScan are empty. 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. We disregard swingline loans since a swingline loan is a sublimit under a revolving line of credit and recording both would result in double counting credit availability. Letter of credit facilities are recorded only if they are standalone lines, but not if they are available under a revolving line of credit.

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 check the contract header, the signature page and commitment schedules to ensure 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, collateralized loan obligation, investment manager, mutual fund, business development company, other, real estate investment trust, government, individual, and "other". 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. "Other" lenders primarily include nonfinancial corporations. Contracts entered into with "other" lenders 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, DealScan
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 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,	Manual collection,

	zero otherwise	DealScan
Syndicated	Indicator equals one if the debt is a syndicated loan, zero otherwise	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 (CHE) divided by total assets	Compustat, Capital IQ
Current ratio	Current assets (ACT) divided by current liabilities (LCT). When unavailable, calculated as (cash (CHE) plus receivables (RECT) plus inventory (INVT) plus other current assets (ACO)) divided by (accounts payable (AP) plus income taxes payable (TXP) plus other current liabilities (LCO) plus debt in current liabilities (DLC))	Compustat, Capital IQ
Coverage ratio	EBITDA divided by interest expense (XINT)	Compustat, Capital IQ
EBITDA	Earnings before interest, taxes, depreciation and amortization (EBITDA)	Compustat, Capital IQ
EBITDA < 0	Indicator equals one if EBITDA is negative, zero otherwise	Compustat, Capital IQ
Firm age	Number of years elapsed since the firm was founded	Capital IQ, EDGAR 10-K filings
Inventory	Inventory (INVT) divided by total assets	Compustat, Capital IQ
Leverage	Long-term debt (DLTT) plus debt in current liabilities (DLC) divided by total assets	Compustat, Capital IQ
Market-to-book	Common shares outstanding (CSHO) times stock price (PRCC_F) plus preferred stock (PSTK) plus long-term debt (DLTT) plus debt in current	Compustat, Capital IQ

	liabilities (DLC), divided by total assets	
Δ Profitability	Annual change in the ratio of EBITDA to total assets	Compustat, Capital IQ
Receivables	Receivables (RECT) divided by total assets	Compustat, Capital IQ
Research expense	Research expense (XRD) divided by total assets	Compustat, Capital IQ
Sales growth	Sales in year *t* divided by sales in year *t*-1 minus one	Compustat, Capital IQ
PP&E	Net property, plant and equipment (PPENT) divided by total assets	Compustat, Capital IQ
Total Assets	Total book assets (AT)	Compustat, Capital IQ
Volatility	Daily standard deviation in the firm's stock returns between calendar days -485 and -120 prior to origination date, multiplied by the square root of 252. At least 120 days of returns must be available.	CRSP

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, and Δ profitability measures are capped at a maximum value of one and the minimum value for Δ profitability is set to minus one to eliminate outliers that persist after winsorization.

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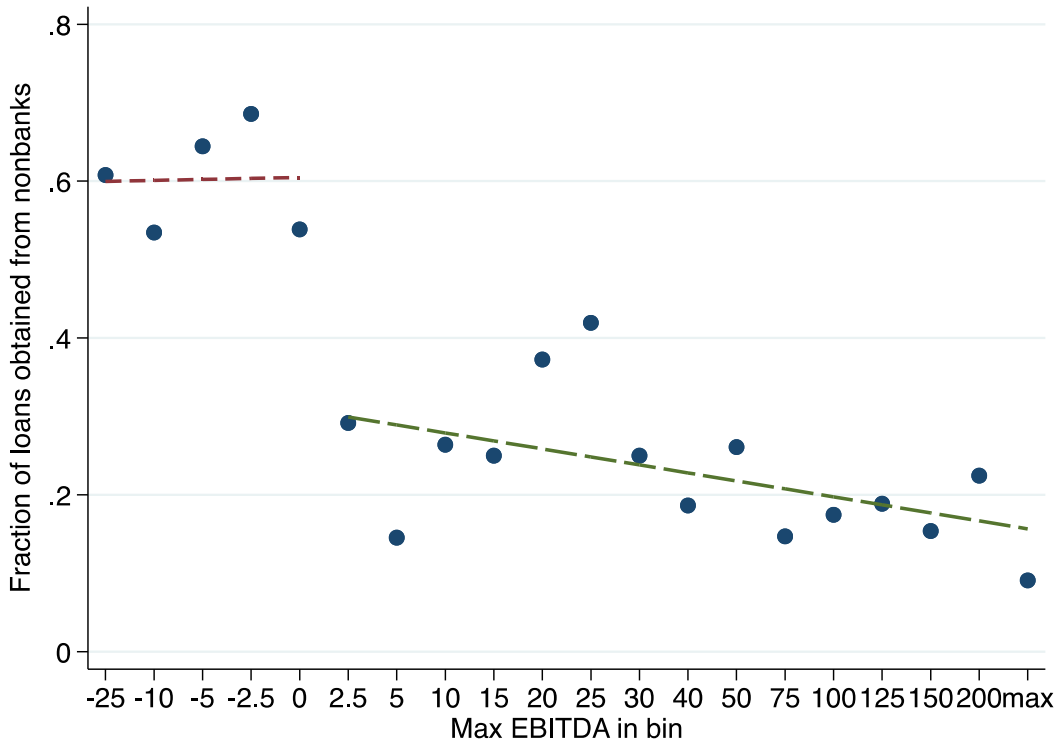


Figure 1: Fraction of loans obtained from nonbanks by EBITDA bin
This figure shows what fraction of loans is obtained from nonbanks at different levels of EBITDA. Loans are allocated into twenty bins based on the borrower's EBITDA at the end of the fiscal year prior to loan origination. The x-axis shows the upper limit of the EBITDA for each bin. The choice of bin limits roughly follows the distribution obtained by splitting EBITDA into twenty quantiles, rounded to symmetric numbers.

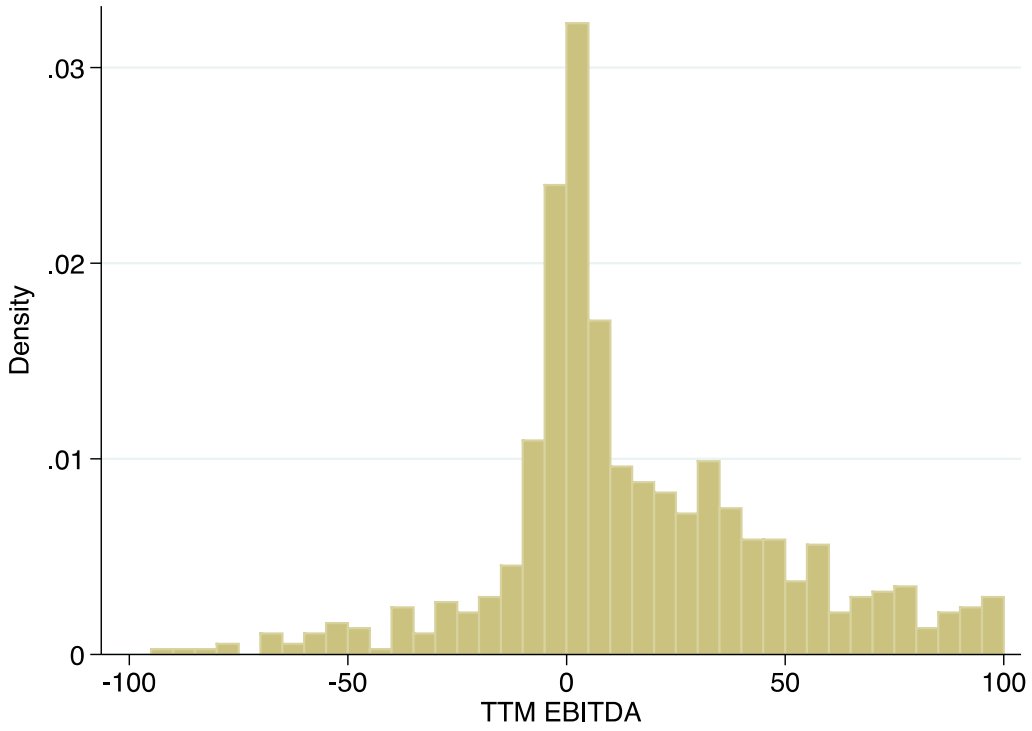


Figure 2: Histogram of trailing twelve month EBITDA
This figure shows a histogram of trailing twelve month EBITDA for those borrowers whose EBITDA is within the range of minus 100 million dollars to plus 100 million dollars. Bin width is five million dollars. The sample includes all borrowings of a random sample of 632 middle-market firms originated and filed with the SEC during the 2010-2015 period.

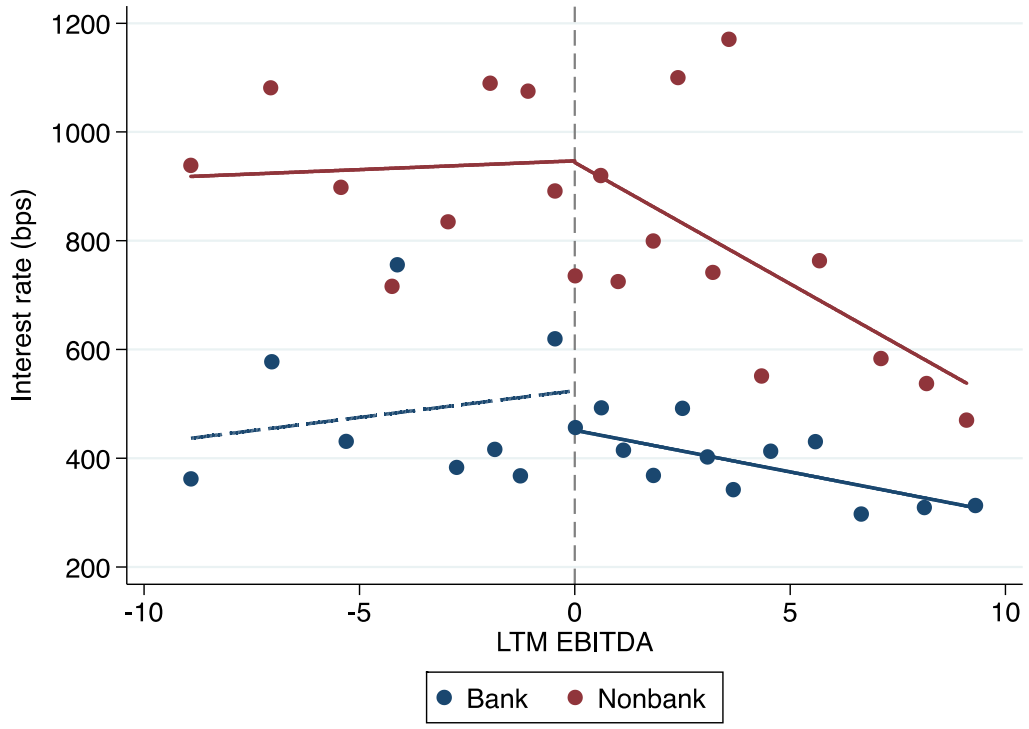


Figure 3: Relation between interest rate and EBITDA in the neighborhood of zero EBITDA

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 $10 million and plus $10 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 of these 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	219	28.77
2012	202	32.67
2013	165	32.12
2014	173	30.06
2015	99	35.35
Total observations	1,047	31.33

Panel B: Nonbank lender types and DealScan match rates

	Obs.	% of nonbank deals	% tracked in DealScan
Bank FCO	31	9.45	29.03
FCO	86	26.22	22.09
Investment bank	39	11.89	76.92
Insurance	14	4.27	7.14
BDC	11	3.35	9.09
PE/VC	60	18.29	0.00
Hedge fund	57	17.38	7.02
Investment manager	25	7.62	8.00
Other	5	1.52	0.00
Total observations	328	100.00	20.43

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 borrowings of a random sample of 632 middle-market firms originated during the 2010-2015 period. Multiple tranches within a given package are treated as a single observation. 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	325	295.3808 (436.5081)	715	571.3228 (996.8841)	-275.9420*** (-6.21)
EBITDA	325	18.0979 (66.1373)	713	68.5232 (170.4198)	-50.4253*** (-6.85)
Leverage	323	0.3586 (0.2834)	714	0.2619 (0.2336)	0.0967*** (5.36)
Market-to-book	292	1.7853 (1.7402)	665	1.5358 (1.2679)	0.2494** (2.21)
Research expense	325	0.0908 (0.2031)	715	0.0365 (0.0890)	0.0544*** (4.63)
PP&E	325	0.2588 (0.2598)	715	0.2737 (0.2624)	-0.0149 (-0.85)
Cash	325	0.1739 (0.2240)	715	0.1445 (0.1556)	0.0294** (2.14)
Receivables	325	0.1507 (0.1334)	711	0.1506 (0.1208)	0.0001 (0.02)
Inventory	324	0.1185 (0.1513)	708	0.1331 (0.1698)	-0.0147 (-1.39)
Firm age	328	28.7973 (27.6406)	719	38.0834 (33.1575)	-9.2862*** (-4.73)
Sales growth	303	0.1378 (0.3993)	704	0.1258 (0.3138)	0.0120 (0.47)
Volatility	226	0.7275 (0.3781)	599	0.5396 (0.2745)	0.1879*** (6.82)
Deal size	328	72.7655 (188.1610)	718	184.6182 (328.9027)	-111.8528*** (-6.96)
Maturity	326	3.8517 (2.4380)	709	3.9746 (2.0594)	-0.1229 (-0.79)
Fixed rate loan	321	0.5499 (0.4932)	702	0.0410 (0.1916)	0.5090*** (17.88)
Initial interest rate (bps)	315	827.4553 (393.2569)	664	333.6135 (175.8485)	493.8418*** (21.30)
Senior	328	0.6890 (0.4636)	717	0.9763 (0.1523)	-0.2873*** (-10.96)
Second lien	328	0.0483 (0.2113)	719	0.0046 (0.0657)	0.0436*** (3.66)
Secured	328	0.8216 (0.3824)	701	0.8521 (0.3543)	-0.0305 (-1.22)
Performance pricing	328	0.0592 (0.2242)	719	0.3442 (0.4658)	-0.2850*** (-13.36)
Upfront fee (bps)	259	42.0524 (88.8098)	631	17.6745 (41.7340)	24.3779*** (4.23)

	Nonbank loans		Bank loans		Difference
	Obs.	Mean (St. dev.)	Obs.	Mean (St. dev.)	in means (t-statistic)
Annual fee (bps)	258	3.7428 (27.7488)	636	1.8159 (9.0805)	1.9268 (1.09)
Financial covenants	328	0.4970 (0.5008)	719	0.8567 (0.3506)	-0.3598*** (-11.76)
Warrants	328	0.2409 (0.4283)	717	0.0167 (0.1284)	0.2241*** (9.29)
Convertible	328	0.1433 (0.3509)	717	0.0028 (0.0528)	0.1405*** (7.21)

Table 3: Probability of borrowing from a nonbank lender

This table reports marginal effects from Probit regressions of whether a loan is extended by a nonbank lender. 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. All regressions control for year fixed effects. Column 5 controls for borrower fixed effects and limits the sample to firms that borrow from both bank and nonbank lenders. z-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)
Ln(Assets)	-0.0222	-0.0053	-0.0049	-0.0088	0.1153
	(-1.25)	(-0.30)	(-0.27)	(-0.48)	(1.23)
EBITDA	-0.0012***	-0.0006	-0.0007***	-0.0008***	-0.0004
	(-3.53)	(-1.54)	(-2.58)	(-2.67)	(-0.42)
EBITDA squared	0.0000***	-0.0000			
	(3.19)	(-0.27)			
EBITDA < 0		0.2528***	0.2505***	0.2778***	0.5980***
		(4.75)	(4.78)	(5.61)	(2.64)
Leverage	0.4105***	0.3831***	0.3859***	0.4220***	0.4619
	(4.33)	(3.88)	(3.90)	(4.58)	(1.20)
Market-to-book	0.0019	0.0024	0.0025	0.0001	-0.0325
	(0.12)	(0.17)	(0.17)	(0.01)	(-0.49)
Research expense	0.4878***	0.3164*	0.3154*	0.2890*	0.4673
	(3.05)	(1.93)	(1.91)	(1.70)	(0.39)
PP&E	0.0667	0.1106	0.1090	0.0729	0.5573
	(0.68)	(1.16)	(1.14)	(0.73)	(1.38)
Current ratio	-0.0032	-0.0049	-0.0050		-0.0584
	(-0.27)	(-0.38)	(-0.39)		(-1.13)
Cash				-0.0683	
				(-0.51)	
Receivables				0.1208	
				(0.55)	
Inventory				-0.3448**	
				(-2.20)	
Ln(Firm age)	-0.0533**	-0.0325	-0.0326	-0.0169	-0.9713
	(-2.24)	(-1.40)	(-1.40)	(-0.65)	(-1.46)
Year effects	Yes	Yes	Yes	Yes	Yes
Borrower effects	No	No	No	No	Yes
Observations	951	951	951	944	311

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 three group: 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. Model 2 is the same as Model 1 but drops 30 observations involving bank-affiliated FCOs. The full model is estimated, but only the results for non-affiliated FCOs are tabulated. Model 3 allows for four nonbank groups: 1) FCO or bank-affiliated FCO; 2) investment bank; 3) BDC, PE, or VC; and 4) HF or IM. The full model is estimated, but only the results for BDCs, PEs, and VCs as well as HFs and IMs are tabulated. All regressions control for year fixed effects. 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	Bank FCO	Unaffiliated FCO	BDC / PE / VC	Hedge fund / IM
Ln(Assets)	1.0389	1.9852**	0.7656**	1.0843	1.0154	0.7108***	0.8184
	(0.31)	(2.36)	(-2.50)	(0.43)	(0.11)	(-2.73)	(-1.55)
EBITDA	0.9932**	0.9971	0.9911**	0.9924**	0.9937**	0.9914	0.9905**
	(-2.29)	(-1.07)	(-2.04)	(-2.15)	(-2.04)	(-1.44)	(-2.20)
EBITDA < 0	2.1631**	4.2233***	4.0368***	1.7547	2.3586**	3.9768***	4.3493***
	(2.30)	(3.21)	(4.58)	(1.10)	(2.17)	(3.23)	(3.86)
Leverage	6.0637***	5.2706*	13.2532***	8.2290***	5.0982***	5.1155**	21.9652***
	(3.31)	(1.77)	(4.74)	(2.83)	(2.64)	(2.21)	(5.50)
Sales growth	0.6137	0.8437	1.5035	1.1455	0.4940*	2.0399*	1.2164
	(-1.47)	(-0.32)	(1.31)	(0.26)	(-1.85)	(1.72)	(0.53)
Research expense	5.0367	0.0568	9.0366**	0.4106	6.5337	33.8749***	1.0679
	(1.42)	(-0.95)	(2.33)	(-0.31)	(1.63)	(3.20)	(0.05)
PP&E	1.9118	0.3049	0.7401	10.7198**	0.8744	0.5726	0.8765
	(0.96)	(-1.40)	(-0.43)	(2.29)	(-0.18)	(-0.77)	(-0.14)
Cash	0.7350	0.6637	0.3015	0.1616	0.7538	0.2343	0.3642
	(-0.31)	(-0.29)	(-1.28)	(-0.88)	(-0.25)	(-1.06)	(-0.94)
Receivables	1.9534	0.5572	1.7533	72.6036*	0.4014	1.0665	2.8065
	(0.44)	(-0.25)	(0.44)	(1.90)	(-0.48)	(0.05)	(0.66)

Inventory	0.3820	0.0189**	0.1152*	0.7307	0.3004	0.0235***	0.2262
	(-1.27)	(-2.46)	(-1.84)	(-0.21)	(-1.52)	(-2.98)	(-1.10)
Ln(Firm age)	0.9891	0.7820	0.9657	1.0230	0.9961	1.2891	0.8137
	(-0.06)	(-0.94)	(-0.20)	(0.09)	(-0.02)	(1.27)	(-1.02)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-zero obs. in category	107	36	141	31	76	60	81
Total observations	972	972	972	972	972	972	972

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. Δ profitability is the change in profitability from the previous year to the fiscal year end prior to loan origination. *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	484.5460***	394.0749***	229.4903***	231.4309***	196.4678***			301.2031***
	(13.18)	(10.19)	(8.01)	(6.37)	(7.39)			(5.91)
Bank FCO						-40.2275	-22.6013	
						(-1.44)	(-0.70)	
FCO						248.8545***	217.7476***	
						(5.73)	(5.08)	
Investment Bank						208.3997***	149.0024***	
						(4.56)	(3.55)	
PE/VC/BDC						472.6592***	400.3084***	
						(8.19)	(6.98)	
Hedge fund/IM						425.4771***	422.7661***	
						(8.13)	(8.52)	
Ln(Amount)			-14.3266	-21.7243	10.5089	-17.8483	6.2988	-19.5414
			(-1.12)	(-1.57)	(1.33)	(-1.48)	(0.84)	(-0.76)
Performance			-60.1146***	-35.2793**	-50.2803***	-59.2988***	-47.4231***	-42.4370
pricing			(-4.00)	(-2.19)	(-3.91)	(-4.40)	(-4.10)	(-1.19)
Upfront fee				0.6879***				
				(3.04)				
Annual fee				0.7695**				
				(2.26)				
Warrants			101.0609***	101.4008**	66.6420	60.5243	22.4374	50.9996
			(2.62)	(2.25)	(1.56)	(1.60)	(0.58)	(0.54)
Convertible			-235.4267***	-235.8463***	-154.2246**	-269.1736***	-162.7110**	-234.6005**
debt			(-3.73)	(-3.73)	(-2.02)	(-4.16)	(-1.99)	(-2.04)
Financial			-10.3650	-22.2795	-22.8911	13.7500	2.0706	42.8546
covenants			(-0.38)	(-0.79)	(-0.79)	(0.55)	(0.08)	(0.80)
Security			30.0334	23.2605	26.0080	48.4489*	46.1953***	-15.0598
			(1.02)	(0.79)	(1.31)	(1.82)	(2.63)	(-0.21)
Second lien			360.2327***	332.2667***	397.3954***	347.9503***	400.2088***	282.6419***
			(5.23)	(4.36)	(5.61)	(5.11)	(4.86)	(2.95)

Maturity			-7.2178	-7.4092	-7.8630	-2.2428	-3.4949	1.2572
			(-1.38)	(-1.38)	(-1.62)	(-0.43)	(-0.67)	(0.14)
Fixed rate loan			232.3508***	213.7623***	193.4140***	174.7772***	145.0859***	161.2487**
			(6.41)	(5.37)	(5.07)	(5.31)	(3.98)	(2.43)
Seniority			-130.1661**	-142.7078**	-113.7783***	-80.9189*	-66.7228*	-64.9895
			(-2.46)	(-2.31)	(-3.07)	(-1.89)	(-1.77)	(-0.73)
Ln(Assets)		-41.0972***	-11.6308	-0.9138	-36.3044***	-8.6315	-35.0663***	6.4079
		(-5.08)	(-1.03)	(-0.07)	(-3.61)	(-0.76)	(-3.83)	(0.17)
EBITDA		-0.0490	-0.0350	-0.0722	-0.0121	-0.0449	-0.0065	-0.0522
		(-1.00)	(-0.82)	(-1.31)	(-0.45)	(-1.00)	(-0.25)	(-0.63)
EBITDA < 0		148.4939***	117.6728***	93.9362***	102.6255***	107.2269***	91.5718***	70.4539
		(4.24)	(3.84)	(2.72)	(3.63)	(3.80)	(3.59)	(1.14)
Leverage		177.9931***	158.2368***	177.2167***	188.7924***	158.3013***	190.0368***	150.1696*
		(4.03)	(4.37)	(4.76)	(4.11)	(4.49)	(4.15)	(1.90)
Research		-4.8270	-38.0425	13.3192	73.2676	-109.2238	29.9737	-106.4618
expense		(-0.05)	(-0.40)	(0.14)	(0.60)	(-1.37)	(0.28)	(-0.39)
PP&E		-147.6657**	-148.0559**	-137.4255**	-102.1928**	-107.0012**	-71.5943**	131.8308
		(-2.08)	(-2.54)	(-2.25)	(-2.59)	(-2.13)	(-1.97)	(0.77)
Cash		-74.5865	-104.5690	-74.2179	-51.8183	-71.2405	-29.7919	-5.8180
		(-0.87)	(-1.45)	(-1.00)	(-0.78)	(-1.10)	(-0.48)	(-0.03)
Receivables		-252.1801**	-189.6014**	-149.9036	-133.5200	-175.5711**	-130.0667*	-247.1528
		(-2.30)	(-2.11)	(-1.55)	(-1.52)	(-2.18)	(-1.70)	(-0.70)
Inventory		-152.3400**	-193.9841***	-219.3788***	-114.4470**	-154.0383**	-73.8586	83.5507
		(-2.15)	(-2.67)	(-2.75)	(-2.07)	(-2.50)	(-1.46)	(0.25)
Ln(Firm age)		-2.2193	-7.6546	-6.8230	-6.2930	-4.4625	-3.7718	68.7365
		(-0.19)	(-0.83)	(-0.69)	(-0.61)	(-0.53)	(-0.39)	(0.49)
Volatility					149.5283***		101.4412***	
					(4.38)		(3.15)	
Growth					42.5199		37.0915	
					(1.28)		(1.22)	
Market-to-book					-6.4540		-9.2643	
					(-0.90)		(-1.31)	
Constant	398.3408***	632.3115***	691.0496***	644.9909***	593.7180***	576.9470***	526.4007***	-30.6691
	(12.13)	(8.28)	(7.21)	(6.32)	(6.75)	(7.16)	(6.15)	(-0.05)
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	971	949	928	795	730	912	716	929

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

This table reports the results from regressions of non-price loan terms on lender type indicators, loan and firm characteristics. Columns 1-4 of Panel A report the results of OLS regressions of loan amounts and maturity. Columns 5-8 of Panel A and Columns 1-8 of Panel B report marginal effects from Probit regressions of indicators of seniority, security, financial covenants, performance pricing, warrants and convertible debt. Columns 1 and 2 of Panel C report Probit regressions of an indicator of fixed rate loans, columns 3-6 of Panel C report OLS regressions of upfront and annual fees, and columns 7 and 8 of Panel C report Probit regressions of an indicator of second lien loans. For the convertible debt regression, the coefficient for Bank FCOs cannot be estimated because there are no Bank FCO loans that are convertible into equity. Similarly, there are no PE, VC, or BDC loans that include performance pricing. 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. Δ profitability is the change in profitability from the previous year to the fiscal year end prior to loan origination. *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)
Dependent variable	Ln (Amount)	Ln (Amount)	Maturity	Maturity	Seniority	Seniority	Security	Security
Estimation method	OLS	OLS	OLS	OLS	Probit	Probit	Probit	Probit
Bank FCO	-0.8451***	-0.5310**	-0.1987	-0.0297	-0.1483***	-0.0892***	0.1071	0.0525
	(-2.65)	(-1.97)	(-0.46)	(-0.07)	(-4.09)	(-3.23)	(1.28)	(0.71)
FCO	-0.8477***	-0.4005***	-0.3190	0.0503	-0.1314***	-0.0924***	0.0915*	0.0084
	(-4.48)	(-3.16)	(-1.14)	(0.20)	(-4.95)	(-4.24)	(1.78)	(0.17)
Investment bank	0.6976**	0.0585	0.6462**	0.4973**	-0.1549***	-0.1336***	0.0700	0.0356
	(2.26)	(0.38)	(2.12)	(2.01)	(-4.16)	(-4.17)	(0.94)	(0.50)
PE/VC/BDC	-1.8782***	-0.5896**	-0.5226*	0.4471	-0.2525***	-0.1631***	-0.0715	-0.1658***
	(-7.46)	(-2.12)	(-1.79)	(1.40)	(-6.86)	(-4.70)	(-1.33)	(-3.24)
Hedge fund/IM	-1.6928***	-0.5164***	-0.9653***	-0.0776	-0.2037***	-0.1156***	-0.1458**	-0.2198***
	(-6.07)	(-2.88)	(-3.17)	(-0.34)	(-4.86)	(-4.33)	(-2.43)	(-4.75)
Ln(Assets)		0.8409***		0.2459***		0.0017		0.0071
		(16.98)		(2.71)		(0.35)		(0.58)
EBITDA		0.0003		-0.0002		0.0005***		-0.0005***
		(0.52)		(-0.62)		(3.41)		(-3.41)
EBITDA < 0		-0.3329**		-0.9388***		0.0164		0.0437
		(-2.57)		(-4.85)		(1.02)		(1.23)
Leverage		0.3456**		-0.4157		-0.0472**		0.1328**
		(2.04)		(-1.31)		(-2.00)		(2.13)
Research expense		1.2035***		-0.3811		0.0226		0.1973
		(2.91)		(-0.72)		(0.52)		(1.11)
PP&E		-0.2112		0.4545		0.0048		0.0303

		(-0.87)		(1.13)		(0.13)		(0.38)
Cash		0.3161		-0.1246		0.0129		0.0225
		(1.17)		(-0.26)		(0.29)		(0.24)
Receivables		1.1503***		-1.1008		-0.0775		0.0526
		(3.03)		(-1.30)		(-1.30)		(0.35)
Inventory		-1.0566***		-1.2694**		-0.0364		-0.1853*
		(-3.18)		(-2.29)		(-0.68)		(-1.83)
Ln(Firm age)		-0.0499		0.0663		-0.0052		-0.0396**
		(-0.95)		(0.85)		(-0.78)		(-2.25)
Constant	3.6367***	-1.1300***	3.5696***	2.4552***				
	(24.82)	(-3.16)	(17.03)	(3.32)				
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	998	998	987	987	997	997	983	983

Panel B: Performance-related non-price terms

Dependent variable	(1) Financial covenants	(2) Financial covenants	(3) Performance pricing	(4) Performance pricing	(5) Warrants	(6) Warrants	(7) Convertible	(8) Convertible
Estimation method	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
Bank FCO	-0.1627*	-0.1646*	-0.0973	-0.0586	0.0781**	0.0435***		
	(-1.92)	(-1.89)	(-1.21)	(-0.73)	(2.54)	(2.79)		
FCO	-0.2595***	-0.1864***	-0.5319***	-0.4295***	0.1116***	0.0347***	0.0436***	0.0191**
	(-4.96)	(-3.36)	(-5.51)	(-4.34)	(4.89)	(3.09)	(2.97)	(2.37)
Investment bank	-0.1570**	-0.2347***	-0.1098	-0.1366*	0.0904***	0.0526**	0.0572***	0.0287**
	(-1.99)	(-3.32)	(-1.41)	(-1.77)	(3.36)	(2.31)	(3.13)	(2.29)
PE/VC/BDC	-0.4315***	-0.3005***			0.1999***	0.0575***	0.0621***	0.0206**
	(-6.66)	(-4.17)			(6.86)	(3.16)	(3.16)	(2.20)
Hedge fund/IM	-0.5020***	-0.4183***	-0.4907***	-0.3760***	0.1414***	0.0512***	0.0711***	0.0246**
	(-7.96)	(-7.18)	(-5.71)	(-4.21)	(5.29)	(2.98)	(3.20)	(2.23)
Ln(Assets)		0.0588***		0.0746***		-0.0049**		-0.0021*
		(4.50)		(4.85)		(-2.05)		(-1.67)
EBITDA		-0.0001		0.0000		-0.0002***		-0.0000
		(-0.73)		(0.07)		(-3.13)		(-0.74)
EBITDA < 0		-0.1062***		-0.0950**		0.0188*		0.0052
		(-2.67)		(-2.05)		(1.69)		(1.14)
Leverage		0.0413		-0.2400***		-0.0077		0.0100*
		(0.58)		(-2.78)		(-0.59)		(1.78)
Research expense		-0.1059		-0.3623		0.0555*		-0.0021
		(-0.89)		(-1.29)		(1.78)		(-0.22)
PP&E		-0.0168		-0.0458		-0.0175		-0.0053
		(-0.18)		(-0.53)		(-1.00)		(-0.48)
Cash		0.0880		-0.0753		-0.0162		-0.0128
		(0.77)		(-0.54)		(-0.60)		(-0.94)
Receivables		0.5264***		-0.0640		-0.0910**		0.0005
		(3.13)		(-0.36)		(-2.26)		(0.04)
Inventory		-0.3706***		-0.2174		-0.0419		-0.0089
		(-3.38)		(-1.56)		(-1.50)		(-0.76)
Ln(Firm age)		0.0055		-0.0343*		-0.0045		-0.0021
		(0.27)		(-1.66)		(-1.27)		(-1.17)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	999	999	928	928	969	969	871	871

Panel C: Other loan terms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Fixed rate loan	Fixed rate loan	Upfront fee (bp)	Upfront fee (bp)	Annual fee (bp)	Annual fee (bp)	Second lien	Second lien
Estimation method	Probit	Probit	OLS	OLS	OLS	OLS	Probit	Probit
Bank FCO	0.1788***	0.1469**	11.5753	2.1152	-0.7946	-1.7096	0.0200*	0.0109
	(2.75)	(2.34)	(1.30)	(0.24)	(-0.71)	(-0.98)	(1.66)	(1.49)
FCO	0.2874***	0.2391***	29.2366***	15.6682	9.7588	8.6271	0.0278***	0.0153**
	(7.33)	(7.20)	(2.59)	(1.30)	(1.29)	(1.22)	(2.98)	(2.35)
Investment bank	0.2773***	0.2884***	67.4293***	58.9638**	-0.9499	-0.3109	0.0395**	0.0217**
	(4.66)	(5.62)	(2.63)	(2.41)	(-1.15)	(-0.27)	(2.44)	(2.12)
PE/VC/BDC	0.4787***	0.3685***	6.9069	-9.9402	-0.0539	-2.4820	0.0213***	0.0167**
	(9.80)	(6.86)	(0.51)	(-0.69)	(-0.03)	(-1.18)	(2.62)	(2.46)
Hedge fund/IM	0.5261***	0.4287***	19.0527	-0.9024	0.5989	-1.6669	0.0198**	0.0150**
	(9.70)	(9.03)	(1.63)	(-0.08)	(0.43)	(-0.99)	(2.53)	(2.28)
Ln(Assets)		-0.0413***		-5.0537**		-0.7849*		-0.0003
		(-4.00)		(-2.39)		(-1.81)		(-0.38)
EBITDA		0.0000		-0.0024		0.0002		-0.0000
		(0.28)		(-0.23)		(0.14)		(-0.29)
EBITDA < 0		0.0330		22.3755***		5.5011**		-0.0083**
		(1.12)		(2.87)		(2.13)		(-1.97)
Leverage		0.0354		11.6131		0.8170		0.0039
		(0.67)		(1.26)		(0.40)		(0.78)
Research expense		-0.0257		-17.6044		-5.0561		-0.0180
		(-0.32)		(-0.77)		(-0.92)		(-1.07)
PP&E		0.1038		-4.3762		3.4257		-0.0041
		(1.45)		(-0.29)		(0.89)		(-0.56)
Cash		0.0815		-12.4280		-1.4558		0.0092
		(0.98)		(-0.99)		(-0.37)		(0.93)
Receivables		-0.0257		-2.4865		-6.3472		-0.0099
		(-0.23)		(-0.09)		(-1.11)		(-0.86)
Inventory		0.0235		-7.7659		-4.4235		0.0093
		(0.27)		(-0.51)		(-0.92)		(1.13)
Ln(Firm age)		0.0003		0.4844		1.8242*		0.0016
		(0.02)		(0.17)		(1.83)		(0.96)
Constant			23.7273***	45.3596**	4.3154*	5.0490		
			(4.53)	(2.04)	(1.91)	(1.31)		
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	976	976	848	848	852	852	861	861

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	42.96	178	347	-0.37***	606.29***
				(-4.90)	(5.27)
Ln(Amount)	37.73	186	354	-0.35***	-0.75
				(-4.61)	(-1.50)
Maturity	47.36	189	395	-0.34***	-2.65**
				(-4.64)	(-2.28)
Seniority	43.34	187	384	-0.36***	-0.10
				(-4.94)	(-0.48)
Security	36.11	180	344	-0.36***	-0.08
				(-4.76)	(-0.44)
Second lien	32.49	178	329	-0.35***	-0.08*
				(-4.51)	(-1.86)
Financial covenants	44.40	189	391	-0.34***	-0.58***
				(-4.69)	(-2.83)
Performance pricing	49.55	193	413	-0.34***	-0.15
				(-4.73)	(-1.16)
Warrants	41.73	186	377	-0.36***	0.32**
				(-4.87)	(2.17)
Convertible	43.86	187	385	-0.35***	0.15
				(-4.89)	(1.38)
Upfront fee	21.75	143	214	-0.36***	86.24**
				(-4.10)	(2.01)
Annual fee	53.34	177	344	-0.39***	21.45**
				(-5.60)	(2.25)
Bankrupt_{t+3}	38.42	166	328	-0.35***	0.02
				(-4.56)	(0.02)
$\Delta\ \text{Profitability}_{t+1}$	40.44	186	368	-0.33***	0.06
				(-4.42)	(0.64)
$\Delta\ \text{Profitability}_{t+2}$	29.36	162	273	-0.37***	0.06
				(-4.28)	(0.29)
$\Delta\ \text{Profitability}_{t+3}$	29.91	129	231	-0.38***	0.27*
				(-4.24)	(1.65)

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 EBITDA. Panel A provides the covariate balance of the sample before and after the matching used to estimate the effect for loan amounts (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)) and EBITDA. 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)	-0.462	0.044	1.333	1.101
EBITDA	-0.384	-0.044	0.195	0.695
Profitability	-0.686	-0.030	4.096	1.140

Panel B: Matching Estimates

	(1)	(2)
	Ln (Amount)	Interest Rate
ATET		
Nonbank Dummy	-0.188*	414.34***
(AI robust *std. errors)*	(0.111)	(28.71)
N (Matched Observations)	908	874
Bias-adj variables	Ln(assets), EBITDA	Ln(assets), EBITDA

Table 9: Probability of bankruptcy for bank versus nonbank loans

This table reports marginal effects from Probit regressions predicting 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. *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	0.0326**	0.0170	0.0110	0.0153
	(2.33)	(1.40)	(0.90)	(1.19)
Ln(Assets)		0.0129***	0.0110**	0.0125*
		(2.59)	(2.07)	(1.70)
EBITDA		-0.0001	-0.0001	-0.0000
		(-0.62)	(-0.85)	(-0.17)
EBITDA < 0		0.0535***	0.0637***	0.0434**
		(3.13)	(3.60)	(2.27)
Leverage			0.0275	-0.0038
			(1.13)	(-0.13)
PP&E			0.0423	0.0504
			(1.24)	(1.39)
Cash			-0.0003	0.0680
			(-0.01)	(1.18)
Receivables			0.0290	0.1106
			(0.30)	(1.25)
Inventory			-0.0340	0.0266
			(-0.66)	(0.63)
Research expense			-0.0368	-0.0330
			(-0.68)	(-0.59)
Ln(Firm age)			0.0051	-0.0018
			(0.69)	(-0.18)
Volatility				0.0492**
				(2.18)
Sales growth				0.0045
				(0.27)
Market-to-book				-0.0133
				(-1.10)
Year effects	Yes	Yes	Yes	Yes
Observations	948	942	929	715

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. *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	-0.0362**	0.0059	0.0062	-0.0030	0.0067	0.0024
	(-2.53)	(0.39)	(0.48)	(-0.26)	(0.51)	(0.19)
Ln(Assets)	-0.0038	0.0027	-0.0036	0.0120**	-0.0030	-0.0032
	(-0.53)	(0.33)	(-0.64)	(2.31)	(-0.50)	(-0.41)
EBITDA	-0.0001	-0.0001	0.0002	-0.0001	-0.0001	0.0002
	(-1.54)	(-1.09)	(1.15)	(-1.50)	(-0.88)	(0.95)
EBITDA < 0	0.1016***	0.0049	0.0342*	0.0389*	0.0237	0.0204
	(4.47)	(0.20)	(1.72)	(1.75)	(0.94)	(1.19)
Leverage	0.1594***	0.0095	-0.0035	-0.0021	0.0134	0.0239
	(3.67)	(0.23)	(-0.11)	(-0.07)	(0.31)	(0.79)
Research expense	0.4349***	-0.0009	0.0050	0.3441*	-0.3087*	0.0963
	(3.35)	(-0.01)	(0.05)	(1.76)	(-1.89)	(0.86)
PP&E	-0.0602	0.0274	0.0056	-0.0302	0.0075	0.0334
	(-1.59)	(0.96)	(0.22)	(-1.44)	(0.29)	(1.52)
Cash	-0.1566**	0.0744	-0.0216	-0.1591**	-0.0326	-0.0366
	(-2.28)	(1.27)	(-0.40)	(-2.56)	(-0.51)	(-0.75)
Receivables	-0.1058	0.0189	0.0022	-0.0760	0.0137	0.0172
	(-1.59)	(0.34)	(0.04)	(-1.32)	(0.19)	(0.39)
Inventory	-0.0645	0.0445	0.0444	0.0578	-0.0319	0.0311
	(-1.57)	(1.30)	(0.94)	(1.51)	(-0.90)	(0.80)
Ln(Firm age)	0.0070	0.0056	0.0025	-0.0007	0.0133	-0.0023
	(1.16)	(0.79)	(0.40)	(-0.14)	(1.53)	(-0.33)
Volatility				0.0109	-0.0080	0.0115
				(0.59)	(-0.34)	(0.39)
Sales growth				-0.0676**	0.0339	0.0196
				(-2.04)	(0.93)	(0.76)
Market-to-book				0.0066	0.0145**	-0.0068
				(0.95)	(2.14)	(-1.25)
Constant	0.0008	-0.0867	-0.0236	-0.0634	-0.0210	-0.0057
	(0.01)	(-1.12)	(-0.57)	(-1.21)	(-0.36)	(-0.09)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	996	925	776	784	736	607

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

	(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]
Bank FCO	-0.0146	0.0159	0.0180	0.0147	-0.0006	0.0129
	(-0.83)	(0.86)	(0.94)	(0.97)	(-0.04)	(0.66)
FCO	-0.0533**	0.0014	0.0112	-0.0101	-0.0117	0.0297*
	(-2.43)	(0.06)	(0.67)	(-0.55)	(-0.49)	(1.79)
Investment bank	-0.0395*	0.0391	-0.0005	-0.0245	0.0198	-0.0040
	(-1.79)	(1.21)	(-0.03)	(-1.07)	(0.66)	(-0.25)
PE/VC/BDC	0.0089	0.0418	-0.0623*	0.0282	0.0203	-0.0859
	(0.28)	(1.41)	(-1.78)	(0.75)	(0.54)	(-1.48)
Hedge fund/IM	-0.0773**	-0.0479	0.0514	-0.0143	0.0212	0.0159
	(-2.55)	(-1.18)	(1.51)	(-0.49)	(0.68)	(0.54)
Ln(Assets)	0.0034	0.0020	-0.0057	0.0135**	-0.0034	-0.0054
	(0.61)	(0.24)	(-0.95)	(2.54)	(-0.54)	(-0.66)
EBITDA	-0.0001*	-0.0001	0.0002	-0.0001	-0.0001	0.0002
	(-1.85)	(-1.09)	(1.18)	(-1.54)	(-0.88)	(1.03)
EBITDA < 0	0.1008***	0.0081	0.0349*	0.0338	0.0232	0.0246
	(4.34)	(0.32)	(1.80)	(1.50)	(0.92)	(1.51)
Leverage	0.1413***	0.0153	-0.0098	-0.0029	0.0100	0.0160
	(3.38)	(0.34)	(-0.30)	(-0.10)	(0.23)	(0.58)
Research expense	0.4499***	-0.0359	0.0548	0.3389*	-0.3151*	0.1581
	(3.48)	(-0.32)	(0.55)	(1.70)	(-1.95)	(1.37)
PP&E	-0.0597	0.0380	-0.0081	-0.0326	0.0140	0.0258
	(-1.58)	(1.27)	(-0.34)	(-1.49)	(0.54)	(1.17)
Cash	-0.1850***	0.0782	-0.0322	-0.1575**	-0.0310	-0.0584
	(-2.89)	(1.32)	(-0.60)	(-2.49)	(-0.47)	(-1.20)
Receivables	-0.0775	0.0299	-0.0246	-0.0785	0.0109	0.0057
	(-1.14)	(0.49)	(-0.47)	(-1.33)	(0.15)	(0.13)
Inventory	-0.0372	0.0561	0.0237	0.0648*	-0.0271	0.0138
	(-0.94)	(1.47)	(0.53)	(1.72)	(-0.75)	(0.34)
Ln(Firm age)	0.0051	0.0049	0.0040	-0.0015	0.0144	-0.0002
	(0.89)	(0.72)	(0.65)	(-0.32)	(1.64)	(-0.03)
Volatility				0.0153	-0.0121	0.0162
				(0.85)	(-0.52)	(0.51)
Sales growth				-0.0705**	0.0344	0.0241
				(-2.12)	(0.94)	(0.93)
Market-to-book				0.0049	0.0142**	-0.0059
				(0.70)	(2.05)	(-0.97)
Constant	-0.0365	-0.0860	-0.0109	-0.0708	-0.0217	0.0015
	(-0.78)	(-1.11)	(-0.26)	(-1.32)	(-0.35)	(0.02)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	979	909	764	769	722	596

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	-0.0267	0.0075	-0.0280	0.0193	0.0144	-0.0222
	(-0.38)	(0.13)	(-0.63)	(0.27)	(0.25)	(-0.48)
Ln(Assets)	0.0015	0.0642***	0.0087	-0.0143	0.0674**	0.0044
	(0.06)	(2.82)	(0.52)	(-0.50)	(2.58)	(0.24)
EBITDA	0.0003**	-0.0001	-0.0002	0.0003***	-0.0000	-0.0001
	(2.18)	(-0.67)	(-1.12)	(2.94)	(-0.31)	(-1.00)
EBITDA < 0	-0.0335	-0.1068	-0.1105*	-0.0306	-0.1393	-0.1242*
	(-0.36)	(-1.32)	(-1.89)	(-0.30)	(-1.60)	(-1.86)
Leverage	0.0895	0.0742	-0.1094	0.0933	0.0795	-0.1100
	(0.55)	(0.45)	(-1.19)	(0.58)	(0.50)	(-1.08)
Research expense	0.3150	0.1805	0.1405	0.1319	0.3369	0.2111
	(0.92)	(0.63)	(0.71)	(0.39)	(1.09)	(1.00)
PP&E	-0.2799**	-0.0806	-0.2261**	-0.3022***	-0.0781	-0.2320**
	(-2.41)	(-0.57)	(-2.32)	(-2.62)	(-0.53)	(-2.28)
Cash	-0.3177	0.1391	-0.2750*	-0.3967	0.1234	-0.2583*
	(-1.46)	(0.73)	(-1.95)	(-1.64)	(0.58)	(-1.69)
Receivables	-0.2090	0.5250	-0.0732	-0.3139	0.5252	-0.1009
	(-0.77)	(1.56)	(-0.43)	(-1.14)	(1.48)	(-0.57)
Inventory	-0.1799	0.0638	-0.2012*	-0.1805	0.1250	-0.2221*
	(-0.96)	(0.30)	(-1.69)	(-0.96)	(0.59)	(-1.79)
Ln(Firm age)	0.0310	0.0189	0.0511**	0.0233	0.0176	0.0425*
	(0.93)	(0.46)	(2.30)	(0.64)	(0.38)	(1.69)
Volatility				-0.0767	0.0244	0.0168
				(-0.66)	(0.21)	(0.22)
Sales growth				-0.0723	-0.0448	-0.0796
				(-0.73)	(-0.36)	(-0.99)
Market-to-book				-0.0153	-0.0229	-0.0095
				(-0.74)	(-1.02)	(-0.56)
Constant	0.0934	-0.3254	0.2425*	0.3481	-0.3318	0.2861*
	(0.43)	(-1.62)	(1.72)	(1.35)	(-1.13)	(1.74)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	827	827	827	789	789	789

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	0.0878	0.0127	-0.0643	0.0917	-0.0054	-0.0463
	(0.45)	(0.12)	(-0.70)	(0.45)	(-0.05)	(-0.48)
FCO	0.0409	0.0431	0.0303	0.0913	0.0518	0.0156
	(0.41)	(0.45)	(0.30)	(0.88)	(0.50)	(0.15)
Investment bank	-0.0306	0.2421	0.0588	-0.0073	0.2422	0.0545
	(-0.23)	(1.48)	(0.80)	(-0.05)	(1.53)	(0.73)
PE/VC/BDC	-0.3022**	-0.1877	-0.2092**	-0.2881**	-0.2102	-0.1767**
	(-2.56)	(-1.45)	(-2.54)	(-2.25)	(-1.60)	(-2.11)
Hedge fund/IM	0.0188	-0.1058	-0.0413	0.1312	-0.0895	-0.0439
	(0.12)	(-1.02)	(-0.55)	(0.80)	(-0.81)	(-0.56)
Ln(Assets)	-0.0071	0.0558**	0.0015	-0.0241	0.0600**	-0.0029
	(-0.25)	(2.41)	(0.09)	(-0.80)	(2.26)	(-0.15)
EBITDA	0.0003**	-0.0001	-0.0002	0.0004***	-0.0000	-0.0001
	(2.45)	(-0.64)	(-1.05)	(3.27)	(-0.31)	(-0.93)
EBITDA < 0	-0.0209	-0.0786	-0.0962	-0.0188	-0.1147	-0.1087
	(-0.22)	(-0.96)	(-1.57)	(-0.18)	(-1.30)	(-1.56)
Leverage	0.0734	0.0725	-0.1184	0.0763	0.0720	-0.1160
	(0.46)	(0.47)	(-1.25)	(0.48)	(0.46)	(-1.13)
Research expense	0.5086	0.2926	0.2514	0.3558	0.4768	0.3028
	(1.42)	(1.00)	(1.18)	(1.00)	(1.52)	(1.33)
PP&E	-0.2972**	-0.0939	-0.2138**	-0.3193**	-0.0946	-0.2236**
	(-2.39)	(-0.72)	(-2.21)	(-2.56)	(-0.69)	(-2.20)
Cash	-0.3422	0.1240	-0.2888**	-0.4548*	0.0854	-0.2835*
	(-1.57)	(0.65)	(-2.08)	(-1.87)	(0.40)	(-1.85)
Receivables	-0.2263	0.5579*	-0.0828	-0.3386	0.5595	-0.1175
	(-0.81)	(1.69)	(-0.48)	(-1.20)	(1.60)	(-0.66)
Inventory	-0.2170	0.0509	-0.2270*	-0.2268	0.1102	-0.2515*
	(-1.16)	(0.25)	(-1.84)	(-1.21)	(0.53)	(-1.93)
Ln(Firm age)	0.0346	0.0196	0.0521**	0.0307	0.0197	0.0449*
	(1.01)	(0.49)	(2.31)	(0.84)	(0.44)	(1.74)
Volatility				-0.0925	0.0376	0.0122
				(-0.75)	(0.33)	(0.16)
Sales growth				-0.0521	-0.0349	-0.0671
				(-0.52)	(-0.28)	(-0.83)
Market-to-book				-0.0159	-0.0225	-0.0100
				(-0.77)	(-0.98)	(-0.57)
Constant	0.1279	-0.3023	0.2667*	0.4007	-0.3242	0.3158*
	(0.58)	(-1.55)	(1.90)	(1.52)	(-1.14)	(1.90)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	812	812	812	774	774	774

Table 11: Announcement returns around loan origination

This table reports cumulative announcement returns around origination of loans by bank versus nonbank lenders. Market adjusted cumulative returns 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 seven calendar days of loan origination. *, **, and *** in the bank and nonbank columns indicate that average cumulative abnormal returns are statistically different from zero at 10%, 5%, and 1%. *, **, and *** in diff columns indicate that average cumulative abnormal returns for nonbank loans are statistically different average cumulative abnormal returns for bank loans at 10%, 5%, and 1%. For medians, the results are based on the Wilcoxon rank-sum test.

	Mean			Median			N	
	Bank	Non-bank	Diff	Bank	Non-bank	Diff	Bank	Non bank
All	0.78%**	2.05%**	1.27%	0.17%	1.36%**	1.19%	391	151
Price >= $5	0.45%	1.55%*	1.10%	0.20%	1.31%*	1.11%*	308	62
Filing delay <= 4 days	0.90%**	3.22%**	2.32%**	0.19%	2.21%***	2.02%**	254	82
Price >= $5 and filing delay <= 4 days	0.33%	1.92%	1.59%	0.10%	2.18%*	2.08%**	205	33

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. 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. Appendix Figure 1 shows the result. Due to computational limitations, we use 500 cluster initiations for each k when producing these graphs.

The top left graph in Appendix Figure 1 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 Appendix Figure 1 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 Appendix Table 1 shows the four-cluster solution and Panel A of Appendix Table 2 shows loan and firm characteristics for the clusters. Despite a lack of a strong distinction between clusters in terms of loan and firm characteristics, the algorithm does strongly separate bank from nonbank loans. There are two clusters dominated by banks and two clusters dominated by nonbanks. Cluster one consists of small senior fixed rate loans to comparatively young firms with high sales growth. Cluster two consists of very large senior floating rate loans, almost always with financial covenants, to large, mature borrowers. Cluster three consists of moderately sized loans that mostly have the structure of a traditional bank loan: floating rate, senior secured, with financial covenants. Borrowers have low leverage and high current ratios. Cluster four consists entirely of junior loans with an average interest rate of 10.2% and borrowers on average have negative cash flow. Clusters one and four have 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, hedge funds, investment managers, and PE/VCs are grouped into clusters one and four. Banks dominate clusters two and three. Bank-affiliated finance companies as well as unaffiliated finance companies are spread throughout the clusters, but have around half of their observations in cluster three. Investment banks cluster especially into large loans (cluster two).

Panels B of Appendix Tables 1 and 2 show the five-cluster solution with characteristics. It is immediately apparent that the two clusters dominated by nonbanks show little change compared to the four-cluster solution. The algorithm breaks a fifth cluster out of the previous clusters two and three. This fifth cluster is almost entirely made up of unsecured bank loans. Borrowers are large and mature and pay low interest rates.

Panels C of Appendix Tables 1 and 2 show the six-cluster solution and corresponding characteristics. There continue to be two clusters dominated by a nonbank (clusters four and five) and one cluster of unsecured bank loans with low interest rates (cluster three). The remaining two bank-dominated clusters from the five-cluster solution get split into three clusters. All three clusters are dominated by senior secured floating rate loans, but they differ in the size of the loans. Cluster one contains loans with an average size of $34 million. Aside from banks, the cluster has primarily has some involvement from finance companies and bank-affiliated finance companies. Cluster two contains very large loans with an average size of $659 million and is almost exclusively served by banks and investment banks. Cluster six contains loans with an average size of $138 million. Primarily lenders are banks, finance companies, and investment banks.

In summary, it is apparent that there are two clusters dominated by alternative vehicles. Adding more clusters tends to result in splitting up the bank-dominated clusters. Investment banks are unique in that they focus on very 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. Appendix Figure 2 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 Appendix Tables 1 and 2 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 high 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 four.

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.

Appendix Table 3 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 and their borrowers have higher leverage. There is marginal evidence that Bank FCOs make smaller loans that are more likely to have a fixed interest rate. 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 if appropriate. 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 larger deals with more highly leveraged firms. Investment managers prefer senior unsecured debt. PE and VC firms make more junior loans to comparatively less levered borrowers. BDCs prioritize first lien secured loans. 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 only two groupings are possible: one group consists of hedge funds and investment managers and the second consists of PE and VC firms as well as BDCs. The second criterion yields the same result. Hedge funds and investment managers share the same sign on six out of eleven coefficients, and PE and VC firms and BDCs share the same sign on eight coefficients. Column 7 tests whether these two groups are indeed significantly different from each other. Compared to hedge funds and investment managers, PE firms, VCs and BDCs are significantly more likely to make junior loans to borrowers with lower leverage. There are also differences just above or just below the 10% significance level in terms of fixed rate loan status, collateral, and sales growth. Thus, it appears appropriate to organize asset managers into the above two groups.

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.

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 just under 60%.

Figure A4 shows a histogram of EBITDA for all sample borrowers whose EBITDA is within an interval of ten million dollars around zero. We use a bin width of one million dollars.

Even when zooming in that closely to the boundary, the histogram is inconsistent with the concern that borrowers might precisely manipulate EBITDA to avoid having to borrow from a nonbank. The bar immediately to the left of zero has almost the same height as the bar immediately to the right of zero and the distribution continues to appear smooth except for a few jumps that are likely due to the paucity of observations. However, these jumps are further away from the boundary and there is no evidence of missing observations to the left of zero.

Following the discussion in Gelman and Imbens (2014), 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. However, for bandwidths of $50 million or less, all predictive power rests with the EBITDA below zero indicator whose coefficient is large and negative. Thus, in the neighborhood of zero, we find no significant relation between the running variable and the probability of treatment except for the discontinuity.

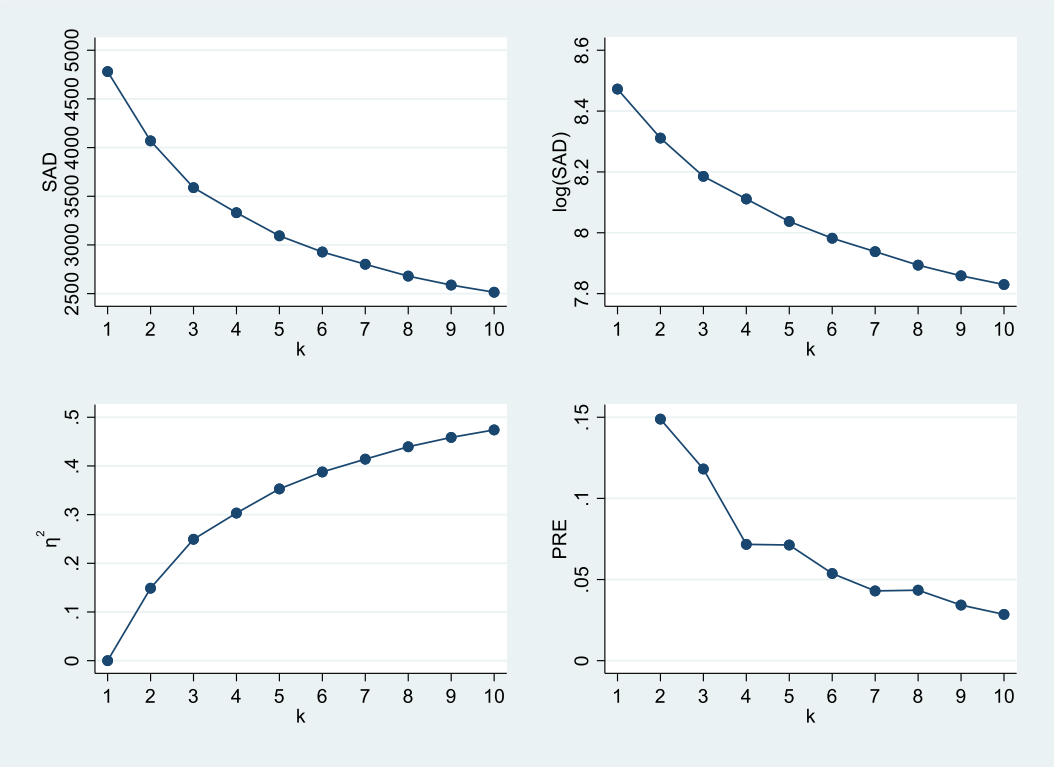


Figure A1: Improvement in the objective function with increasing *k* (all loans)

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).

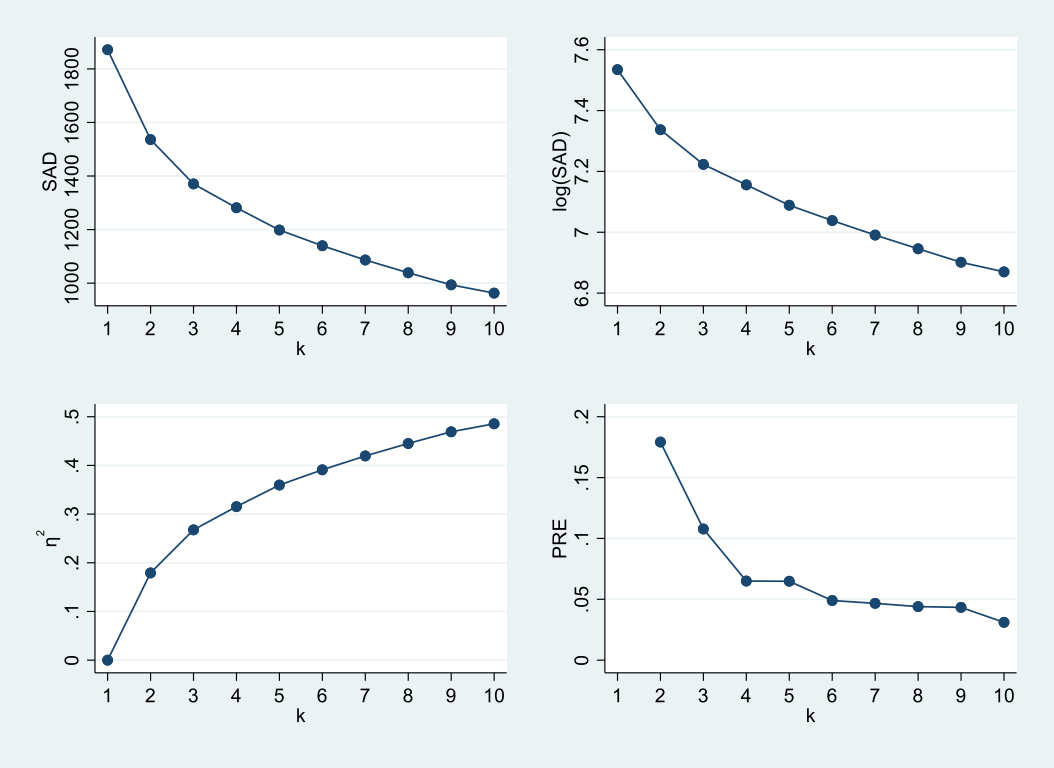


Figure A2: Improvement in the objective function with increasing *k* (excluding bank loans)

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).

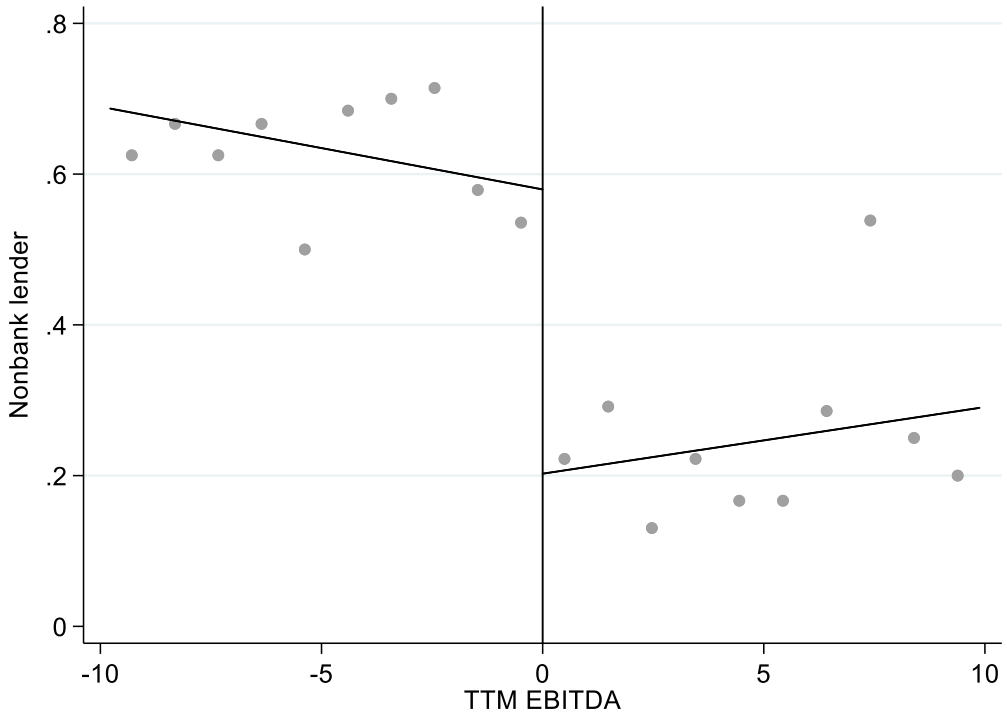


Figure A3: Fraction of loans obtained from nonbanks around the zero EBITDA boundary
This figure shows what fraction of loans is obtained from nonbanks by borrowers whose trailing twelve month EBITDA is between minus $10 million and plus $10 million. Ten even spaced bins are created on either side of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

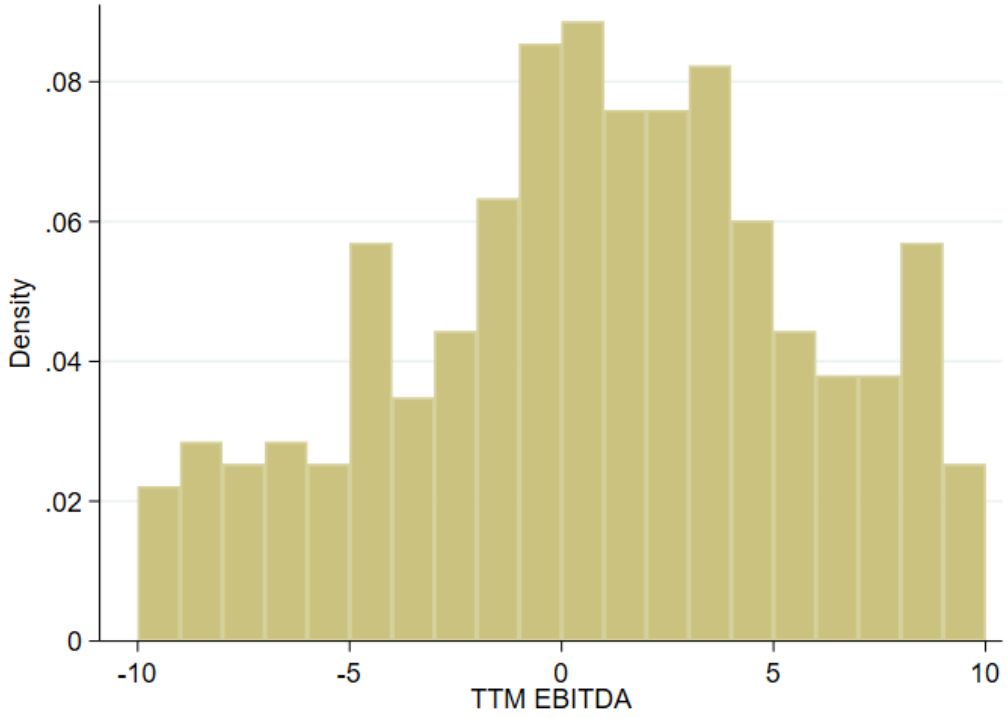


Figure A4: Histogram of trailing twelve month EBITDA around the zero EBITDA boundary

This figure shows a histogram of trailing twelve month EBITDA for those borrowers whose EBITDA is within the range of minus $10 million and plus $10 million. The bin width is one million dollars.

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	0	3	4
Bank	26	271	334	5
Bank FCO	6	4	17	2
FCO	25	10	35	12
Hedge fund	21	3	7	24
Insurance	5	4	0	2
Investment bank	6	19	4	6
Investment manager	16	0	2	5
Other	3	1	1	0
PE/VC	19	0	7	32

Panel B: Five clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
BDC	4	4	3	0	0
Bank	23	5	279	239	90
Bank FCO	6	2	12	7	2
FCO	25	12	33	9	3
Hedge fund	21	23	7	3	1
Insurance	4	2	1	2	2
Investment bank	6	5	3	20	1
Investment manager	16	5	1	0	1
Other	3	0	1	1	0
PE/VC	18	32	7	0	1

Panel C: Six clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
BDC	3	0	0	4	3	1
Bank	221	102	84	22	4	203
Bank FCO	13	0	2	5	2	7
FCO	23	2	3	25	12	17
Hedge fund	6	0	1	21	22	5
Insurance	0	0	2	4	2	3
Investment bank	1	14	1	5	4	10
Investment manager	1	0	1	16	5	0
Other	1	0	0	3	0	1
PE/VC	7	0	1	18	32	0

Panel D: Four clusters, excluding banks

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
BDC	3	5	0	3
Bank FCO	2	1	6	20
FCO	11	23	10	38
Hedge fund	22	21	5	7
Insurance	2	0	4	5
Investment bank	5	3	19	8
Investment manager	5	16	1	1
Other	0	3	1	1
PE/VC	32	18	1	7

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	23.08	386.01	45.92	26.78
Maturity	3.87	5.05	3.29	3.63
Fixed rate loan	0.98	0.02	0.01	0.68
Interest rate	843.95	297.68	413.89	1024.25
Performance pricing	0.00	0.46	0.23	0.01
Senior	1.00	0.99	0.95	0.00
Secured	0.81	0.82	0.90	0.72
Second lien	0.05	0.01	0.00	0.10
Financial covenants	0.30	0.95	0.80	0.50
Warrants	0.26	0.00	0.06	0.29
Convertible debt	0.16	0.01	0.01	0.23
Upfront fee	36.82	16.28	22.56	40.71
Annual fee	4.43	0.95	3.18	2.24
Total assets	201.10	1051.34	192.44	146.16
EBITDA	14.85	144.42	11.67	-4.96
Tangibility	0.26	0.32	0.24	0.19
Leverage	0.31	0.33	0.23	0.43
Firm age	24.72	42.52	33.79	30.57
Volatility	0.80	0.45	0.65	0.74
Market-to-book	1.94	1.52	1.59	1.75
Research expense	0.11	0.02	0.05	0.10
Current ratio	2.11	2.37	2.46	1.73
Sales growth	0.18	0.12	0.12	0.07

Panel B: Five clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Deal size	22.65	24.87	42.83	356.71	243.19
Maturity	3.72	3.55	3.30	5.00	4.23
Fixed rate loan	0.99	0.69	0.01	0.00	0.10
Interest rate	859.09	1033.40	436.36	327.27	225.06
Performance pricing	0.00	0.01	0.21	0.42	0.48
Senior	1.00	0.00	0.95	0.99	0.97
Secured	0.84	0.73	0.99	1.00	0.00
Second lien	0.05	0.10	0.00	0.01	0.00
Financial covenants	0.30	0.50	0.79	0.95	0.84
Warrants	0.27	0.30	0.07	0.00	0.00
Convertible debt	0.17	0.22	0.01	0.01	0.01
Upfront fee	37.94	41.25	26.47	18.77	1.52
Annual fee	4.61	2.27	3.55	0.96	1.07
Total assets	190.30	121.61	168.99	864.59	1091.06

EBITDA	11.85	-6.68	7.37	115.33	153.19
Tangibility	0.26	0.19	0.23	0.33	0.28
Leverage	0.32	0.43	0.22	0.37	0.21
Firm age	24.04	29.89	30.81	40.13	54.31
Volatility	0.81	0.75	0.68	0.49	0.39
Market-to-book	1.95	1.77	1.62	1.38	1.84
Research expense	0.11	0.10	0.06	0.01	0.03
Current ratio	2.03	1.75	2.33	2.33	3.06
Sales growth	0.19	0.07	0.12	0.12	0.10

Panel C: Six clusters

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Deal size	34.48	658.87	200.05	20.61	20.82	138.29
Maturity	2.83	5.05	4.29	3.72	3.43	4.97
Fixed rate loan	0.01	0.01	0.10	0.99	0.72	0.01
Interest rate	479.43	325.30	225.32	864.87	1053.32	316.93
Performance pricing	0.15	0.44	0.49	0.00	0.01	0.39
Senior	0.94	0.99	0.97	1.00	0.00	0.96
Secured	0.99	0.95	0.00	0.84	0.72	1.00
Second lien	0.00	0.01	0.00	0.04	0.08	0.02
Financial covenants	0.76	0.97	0.84	0.30	0.48	0.91
Warrants	0.08	0.00	0.00	0.28	0.31	0.01
Convertible debt	0.01	0.01	0.01	0.17	0.23	0.01
Upfront fee	30.38	26.69	1.63	37.56	41.72	11.50
Annual fee	4.43	0.42	0.81	4.36	1.79	1.41
Total assets	154.38	1703.25	749.11	170.15	114.73	409.54
EBITDA	2.86	225.09	107.52	7.35	-7.06	54.53
Tangibility	0.23	0.40	0.27	0.25	0.19	0.27
Leverage	0.25	0.44	0.19	0.32	0.43	0.25
Firm age	27.55	40.69	56.53	24.11	29.26	40.14
Volatility	0.73	0.46	0.39	0.82	0.76	0.50
Market-to-book	1.64	1.30	1.89	1.97	1.80	1.45
Research expense	0.07	0.01	0.03	0.11	0.10	0.02
Current ratio	2.23	2.31	3.06	2.06	1.69	2.47
Sales growth	0.13	0.12	0.07	0.19	0.08	0.12

Panel D: Four clusters, excluding banks

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Deal size	21.30	18.74	287.34	55.83
Maturity	3.54	2.93	5.39	4.34
Fixed rate loan	0.76	0.95	0.28	0.10
Interest rate	1060.53	982.58	614.93	563.84
Performance pricing	0.01	0.00	0.14	0.10
Senior	0.00	1.00	0.94	0.86
Secured	0.70	0.78	0.87	0.95
Second lien	0.07	0.03	0.09	0.03
Financial covenants	0.44	0.22	0.79	0.69
Warrants	0.32	0.38	0.02	0.13
Convertible debt	0.26	0.23	0.04	0.02
Upfront fee	42.87	36.22	63.62	27.58

Annual fee	1.84	6.29	0.89	5.08
Total assets	117.90	105.89	1039.27	201.78
EBITDA	-7.38	-4.67	124.61	8.02
Tangibility	0.19	0.21	0.40	0.28
Leverage	0.43	0.33	0.48	0.28
Firm age	29.44	18.50	42.68	32.58
Volatility	0.76	0.96	0.59	0.62
Market-to-book	1.78	2.25	1.17	1.68
Research expense	0.10	0.15	0.01	0.06
Current ratio	1.61	1.98	1.87	2.49
Sales growth	0.08	0.25	0.10	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 the ten, five, and one percent levels, respectively.

	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)	-0.0290	-0.0330	0.1393*	-0.0511	-0.0862	-0.0021	-0.0883
	(-1.64)	(-0.30)	(1.68)	(-1.03)	(-1.14)	(-0.05)	(-1.13)
Maturity	0.0037	-0.0259	-0.0354	0.0021	0.0045	0.0289	0.0334
	(0.41)	(-0.42)	(-0.41)	(0.04)	(0.06)	(1.00)	(0.45)
Fixed rate loan	0.0570*	0.0163	0.0449	0.0315	-0.0540	-0.0224	-0.0764
	(1.72)	(0.47)	(0.87)	(1.04)	(-1.10)	(-0.85)	(-1.63)
Initial interest rate	-0.0212	-0.2871***	-0.0346	-0.0442	0.0700	0.0088	0.0788
	(-0.96)	(-5.59)	(-0.56)	(-1.54)	(1.38)	(0.46)	(1.45)
Senior	-0.0810**	-0.0456	0.0158	0.0688***	-0.0770**	-0.0076	-0.0846**
	(-2.34)	(-1.18)	(0.39)	(2.75)	(-2.29)	(-0.41)	(-2.45)
Second lien	0.0121	0.0213	0.0053	0.0215	0.0033	-0.0301**	-0.0268
	(0.46)	(0.87)	(0.20)	(0.80)	(0.12)	(-2.47)	(-0.99)
Secured	0.0048	0.0549	0.0271	-0.0884**	0.0268	0.0345**	0.0613*
	(0.64)	(0.80)	(0.62)	(-2.15)	(0.78)	(2.08)	(1.72)
EBITDA	-0.0072	0.1170	0.1058	-0.1840*	0.1668	-0.0886	0.0782
	(-1.36)	(0.48)	(0.44)	(-1.78)	(0.69)	(-0.89)	(0.27)
Leverage	0.0262**	0.0423	0.0909**	0.0288	-0.1176***	-0.0022	-0.1197***
	(2.36)	(0.89)	(2.43)	(1.00)	(-3.37)	(-0.10)	(-3.25)
Ln(Assets)	0.0193	-0.1060	-0.0213	0.0401	0.0020	-0.0208	-0.0188
	(1.03)	(-0.95)	(-0.33)	(0.85)	(0.04)	(-0.73)	(-0.34)
Growth	-0.0031	-0.0171	-0.0598	-0.0080	0.0503	0.0175	0.0678*
	(-0.33)	(-0.31)	(-1.55)	(-0.27)	(1.30)	(0.78)	(1.69)
Constant	0.0857***	0.4163***	0.4885***	0.2073*	0.1846	0.1196	0.3042*
	(3.15)	(3.46)	(2.87)	(1.78)	(1.06)	(1.50)	(1.72)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	656	102	136	136	136	136	136

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 the ten, five, and one percent levels, respectively.

EBITDA range	[-100,100]	[-50,50]	[-25,25]	[-10,10]	[-5,5]
	(1)	(2)	(3)	(4)	(5)
EBITDA < 0	0.3377***	0.3414***	0.3703***	0.3771***	0.2518**
	(5.41)	(4.97)	(4.80)	(4.00)	(2.10)
EBITDA	-0.0017**	-0.0009	0.0066	0.0088	-0.0219
	(-2.43)	(-0.58)	(1.46)	(0.68)	(-0.81)
(EBITDA < 0)	0.0003	-0.0013	-0.0137*	-0.0198	-0.0313
x EBITDA	(0.16)	(-0.38)	(-1.73)	(-1.06)	(-0.65)
Constant	0.2694***	0.2594***	0.2099***	0.2026***	0.2603***
	(7.47)	(6.30)	(4.50)	(3.26)	(3.15)
Observations	750	617	452	316	211

Table A5: 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

EBITDA range	[-100,100]	[-50,50]	[-25,25]	[-10,10]	[-5,5]
	(1)	(2)	(3)	(4)	(5)
Negative EBITDA	0.3468***	0.3442***	0.3537***	0.3910***	0.2071
	(6.00)	(5.23)	(4.49)	(3.66)	(1.39)
TTM EBITDA	-0.0024**	-0.0016	0.0050	0.0076	-0.0133
	(-2.41)	(-0.73)	(1.10)	(0.59)	(-0.42)
Negative EBITDA x TTM EBITDA	0.0021	-0.0009	-0.0139	-0.0066	-0.0668
	(0.70)	(-0.19)	(-1.62)	(-0.31)	(-1.31)
Ln(Assets)	0.0189	0.0123	-0.0024	0.0133	0.0019
	(0.86)	(0.51)	(-0.09)	(0.42)	(0.06)
Leverage	0.4171***	0.4532***	0.5274***	0.5674***	0.7164***
	(5.04)	(5.32)	(5.57)	(5.31)	(5.37)
Research expense	0.0936	-0.0703	0.1364	0.1352	0.3178
	(0.60)	(-0.44)	(0.86)	(0.66)	(0.68)
Tangibility	0.0753	0.1231	0.0611	-0.0341	-0.1880
	(0.61)	(0.85)	(0.35)	(-0.18)	(-0.79)
Cash	-0.0659	-0.1131	-0.2734	-0.3256	-0.2665
	(-0.48)	(-0.73)	(-1.53)	(-1.50)	(-1.01)
Receivables	0.1650	0.0955	0.0478	0.0456	-0.0495
	(0.76)	(0.42)	(0.20)	(0.17)	(-0.14)
Inventory	-0.3164**	-0.3162**	-0.4087**	-0.3239	-0.0984
	(-2.53)	(-2.25)	(-2.25)	(-1.27)	(-0.32)
Ln(Firm age)	0.0007	0.0162	0.0347	0.0030	-0.0317
	(0.03)	(0.61)	(1.01)	(0.08)	(-0.77)
Constant	0.0170	0.0427	-0.0049	0.0776	0.1908
	(0.11)	(0.27)	(-0.03)	(0.41)	(0.85)
Year effects	Yes	Yes	Yes	Yes	Yes

Industry effects	Yes	Yes	Yes	Yes	Yes
Observations	687	562	412	282	186

Panel B: Second stage

EBITDA range	[-100,100]	[-50,50]	[-25,25]	[-10,10]	[-5,5]
	(1)	(2)	(3)	(4)	(5)
Nonbank	685.3567***	665.1489***	577.3037***	568.8768***	677.9973*
	(6.64)	(5.63)	(4.48)	(3.76)	(1.91)
TTM EBITDA	-0.2297	-0.4656	-4.8636**	-14.4494**	-20.4554
	(-0.34)	(-0.33)	(-2.21)	(-2.18)	(-1.05)
Negative EBITDA x TTM EBITDA	-2.1823	-1.9463	3.5322	20.8306*	62.1680
	(-1.42)	(-0.68)	(0.71)	(1.81)	(1.44)
Ln(Assets)	-49.1861***	-50.6652***	-50.5487***	-46.1641***	-45.6423**
	(-4.03)	(-3.82)	(-3.68)	(-2.82)	(-2.46)
Leverage	16.0056	20.5778	-7.6190	-39.5390	-344.8429
	(0.21)	(0.24)	(-0.08)	(-0.36)	(-1.27)
Research expense	-165.8960*	-198.6625	-281.3085**	-160.9112	-191.6167
	(-1.66)	(-1.56)	(-1.96)	(-1.02)	(-0.73)
Tangibility	-158.4574**	-173.2080**	-129.2343	5.8022	206.2322*
	(-2.05)	(-2.01)	(-1.46)	(0.06)	(1.80)
Cash	-22.8136	6.2665	19.3370	96.3090	152.7841
	(-0.25)	(0.07)	(0.21)	(0.77)	(0.96)
Receivables	-236.6924*	-174.7731	-173.0890	-88.0709	-120.0620
	(-1.68)	(-1.26)	(-1.28)	(-0.50)	(-0.46)
Inventory	-38.4528	-47.2467	-42.7162	-22.7502	-90.0311
	(-0.51)	(-0.60)	(-0.43)	(-0.18)	(-0.56)
Ln(Firm age)	-22.0933	-21.9331	-31.2363*	-19.0898	-0.9700
	(-1.45)	(-1.34)	(-1.77)	(-0.88)	(-0.03)
Constant	729.3411***	727.8023***	845.1979***	738.1461***	732.9964***
	(7.52)	(7.37)	(8.40)	(5.77)	(3.79)
Year effects	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes
Observations	687	562	412	282	186