Nonbank Lending

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ABSTRACT

We provide novel systematic evidence on the terms of direct lending by nonbank financial institutions. Analyzing hand-collected data for a random sample of publicly-traded middle-market firms during the 2010-2015 period, we find that nonbank lending is widespread, with 32% of all loans being extended by nonbanks. Nonbank borrowers are smaller, more R&D intensive, and significantly more likely to have negative EBITDA. Firms are also more likely to borrow from a nonbank lender if local banks are poorly capitalized and less concentrated. Nonbank lenders are less likely to monitor by including financial covenants in their loans, but appear to engage in more ex-ante screening. Controlling for firm and loan characteristics, nonbank loans carry about 200 basis points higher interest rates. 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 techniques and cater to different types of borrowers.

Keywords: shadow banking, relationship lending, market segmentation

JEL Classification: G21, G23, G30, G32

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1 Introduction

Privately placed debt is an important source of financing to informationally opaque firms, yet little is known about who, other than banks, provides capital to such firms and at what terms. Do different types of intermediaries specialize in lending to different types of borrowers? If so, what explains such specialization? How do different lenders set the price and nonprice terms of the debt financing they provide? Do all lenders use the same lending techniques, or do some rely more on screening borrowers ex ante while others monitor borrower behavior ex post? These questions go to the heart of theories of financial intermediation, but are largely unexamined by the existing literature.

This paper provides novel systematic evidence on the sources and terms of private debt financing during the post crisis period. Following the incremental debt choice approach of Denis and Mihov (2003), 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 make up the middle 50% of firms in COMPUSTAT and account for about one third of all U.S. jobs and of private sector GDP.[1] These are the firms that according to theory (Diamond (1991a)) are most likely to rely on monitoring to alleviate moral hazard problems. Middle-market firms are generally not large enough to have credit ratings and access to market-based debt financing (Faulkender and Petersen (2005)), but are required by law to disclose the terms of their credit agreements in SEC filings, thereby allowing us to study both the price and non-price terms negotiated by different types of lenders.

We start by documenting the prevalence of direct nonbank lending, cases where a nonbank financial institution negotiates directly with the borrower rather than participating in a syndicate led by a commercial bank. Such nonbank lending is widespread: About one third of all commercial and industrial loans taken out by publicly-traded middle-market firms during the 2010-2015 period were extended by nonbanks. These lenders represent a variety of financial institutions including finance companies (FCOs), private equity/venture capital (PE/VC) firms,

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

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 about half of bank loans and almost none of the loans extended directly by nonbank lenders.

After establishing the prevalence of nonbank lending, we explore the characteristics of firms that borrow from nonbank lenders versus banks. Compared to firms that borrow from banks, nonbank borrowers are smaller, younger, less profitable, more R&D intensive, and subject to greater stock return volatility. Profitability is a particularly important driver of the choice of lender. Firms with small negative EBITDA are 32% more likely to borrow from a nonbank lender than are firms with small positive EBITDA. This finding suggests a certain degree of market segmentation with banks finding it costly to lend to unprofitable firms since such loans are classified as "substandard" by the regulators.[2] It also indicates that banks are not necessarily special in lending to borrowers subject to informational and moral hazard problems (Carey, Post, and Sharpe (1998), Denis and Mihov (2003)).

We also relate the propensity to borrow from a nonbank lender to the conditions in the firm's local banking market. We find that if banks with branches in a given county are better capitalized, firms headquartered in that county are less likely to turn to nonbank lenders for funding. Although it is difficult to establish causality, these results hold controlling for a wide array of other variables capturing local economic conditions. The strength of the relation between capitalization of local banks and the propensity to borrow from nonbanks is economically important. A one percentage point increase in the tier 1 leverage ratio of such banks is associated with a 6-7% decline in the probability of borrowing from a nonbank lender. Our results thus point to the importance of local credit supply shocks not only for small privately-held firms, as shown recently by Chen, Hanson, and Stein (2017) and Cortes et al (2018), but also for medium-size publicly-traded firms.

Firms are less likely to borrow from a nonbank lender if the local banking market is more concentrated. An increase in the HHI of local deposit concentration of 0.10 is associated with a 3-4% decline in the probability of borrowing from a nonbank lender. Our results are consistent

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

with the recent theoretical model of Donaldson, Piacentino, and Thakor (2017). In their model, nonbanks' higher cost of capital acts as a commitment device to lend only to innovative firms. When bank competition is weak, banks internalize the benefits of lending to and monitoring innovative firms, leaving less room for nonbanks to enter. When bank competition is strong, on the other hand, banks lend to safe firms at a low cost, while nonbanks lend to riskier, more innovative firms.

Turning to the matching between borrowers and different types of nonbank lenders, we find that asset managers are especially likely to lend to unprofitable and levered firms, while private equity and venture capital firms lend to faster growing, R&D-intensive firms. Insurance companies and bank-affiliated finance companies specialize in different types of asset-backed lending. While insurance companies lend to firms with high PPE, bank-affiliated FCOs lend to firms with a lot of receivables.

How do the price and nonprice terms vary across loans extended by different types of lenders? Controlling for observable firm and loan characteristics, including maturity and interest rate exposure, nonbank loans carry about 196 basis points higher initial interest rate than bank loans. This difference cannot be explained by differences in observable borrower characteristics such as leverage, profitability, size, age, or growth or by other loan terms. The difference in interest rates is largest at around 430-450 basis points for loans extended by hedge funds, private equity, and venture capital firms. Why would nonbank borrowers pay higher interest rates on their loans? It may be that these firms are riskier on dimensions that are not observable to econometricians. If they are, then we should see nonbank borrowers being more likely to file for bankruptcy and experiencing worse operating performance following loan origination. This is not what we find. Controlling for observable firm characteristics, nonbank loans do not experience higher bankruptcy rates or worse operating performance. This suggests that differences in interest rates are more likely to be driven by market segmentation and low bargaining power of nonbank borrowers.

We next look at a large number of nonprice terms including maturity, security, presence of financial covenants, and warrants. Except for insurance companies that similarly to banks have stable long-term funding and therefore tend to lend at long maturities, the other nonbank lenders in our data, hedge funds in particular, tend to rely on less stable, shorter term funding. To better match the effective maturity of their liabilities, these nonbanks lend at shorter maturities to borrowers that cannot borrow long-term due to asymmetric information and moral hazard considerations (Diamond (1991b)). Importantly, with the exception of insurance companies, differences in maturity across nonbank lender types disappear once we control for firm characteristics. Thus, maturity appears to be determined primarily by firm fundamentals, with lenders and borrowers matching based on what would be the optimal debt maturity for a given borrower.

Nonbank loans are 37 percentage points less likely to include financial covenants. Instead of ex-post monitoring through financial covenants, which may be difficult to set accurately for unprofitable, R&D-intensive firms, nonbank lenders try to align incentives through the use of warrants and engage in significant ex-ante screening. We find that origination of nonbank loans is associated with significantly higher positive abnormal announcement returns than origination of bank loans. The results on contract terms and announcement returns suggest that bank and nonbank lenders may utilize different lending techniques. While banks appear to rely more heavily on ex-post monitoring of more stable borrowers through financial covenants, nonbank lenders may rely more on ex-ante screening and alignment of incentives.

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

We also estimate the causal effect of borrowing from a nonbank lender on various loan characteristics. The discontinuity in the probability of borrowing from a nonbank lender around zero EBITDA allows us to implement a fuzzy regression discontinuity design (fuzzy RDD) to estimate this causal effect of borrowing from a nonbank lender on various price and non-price terms. While the average difference in interest rates between bank and nonbank loans, controlling for observable firm characteristics, is around 200 basis points, this difference is about

565 basis points at the zero EBITDA threshold. This larger difference in interest rates is due to asset managers driving the results around the zero-EBITDA cutoff. Similarly, using fuzzy RDD, we find that nonbank loans are 58 percentage points less likely to include financial covenants and 42 percentage points more likely to include warrants. We find similar results using nearest neighbor matching based on Mahalanobis distance.

Overall, our results provide evidence of market segmentation in the commercial loan market, where bank and nonbank lenders utilize different lending techniques and cater to different types of borrowers. Lender specialization appears to be driven at least in part by funding stability. Insurance companies and banks lend at longer maturities to less risky firms, while hedge funds lend at shorter maturities to riskier firms. These differences are further correlated with the use of financial covenants and warrants to help mitigate moral hazard problems.

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

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

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

The rest of the paper is organized as follows. Section 2 introduces our sample, discusses the data collection process, and presents summary statistics. Section 3 compares the characteristics of firms borrowing from different types of lenders and also relates the propensity to borrow from nonbank lenders to the conditions in the local banking markets where borrowers operate. In Section 4, we analyze differences in both price and non-price term between bank and nonbank loans. We also present our results utilizing a fuzzy regression discontinuity design well as matching techniques. Section 5 explores the ex post performance of loans in our data. 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 their commercial loans to providers of standard databases such as DealScan or Leveraged Commentary and Data (LCD). As a result, our loan data are largely hand collected and supplemented with DealScan whenever loans are in fact reported in DealScan.

We draw a random sample of 750 publicly-traded US-based middle market firms that appear in Compustat at least once during the 2010-2015 period.[3] Following the definition used by the National Center for the Middle Market, middle market firms are firms with revenues between \$10 million and \$1 billion.[4] Unlike EBITDA-based definitions frequently used by lenders in the leveraged loan market, this revenue-based definition allows us to include unprofitable firms in the analysis. Consequently, our sample is a more heterogeneous and representative set of mid-sized, publicly-traded firms than one could obtain from extant databases that typically focus on the leveraged loan market. To focus on firms that are likely to have entered into significant debt contracts, we require our firms to report book leverage of at least five percent at some point during the 2010-2015 period. Financial firms and utilities are excluded.

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

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

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

To economize on manual data collection, we first attempt to match all contracts to DealScan based on the origination dates and identities of borrowers and lead lenders. Note that our sample includes bank loans, for which the match rate is still only 54% of the total number of bank loans in our sample. For nonbank loans, the match rate to DealScan drops to 20%, with most of the matched loans arranged by investment banks (see Panel B of Table 1). For hedge funds and PE/VC firms the match rates are 6.5% and zero.

For matched contracts, we extract loan characteristics from DealScan. For the remaining contracts, we read the credit agreements and record their characteristics, including amount, maturity, interest rate, fees, priority, security, convertibility, presence of financial covenants, performance pricing, or warrants, and the tranche structure if it exists. Interest rates are recorded as follows. For fixed-rate loans, we record the interest rate as stated in the contract. For floating-rate loans, we record the spread over the London Interbank Offered Rate (LIBOR).[5] We also calculate the loan's initial interest rate as either the fixed rate specified in the contract or the level of LIBOR as of the origination date plus the stated spread. If a contract stipulates an interest rate floor, we use the greater of the calculated interest rate and the floor. Appendix A provides more detail on sample construction and coding of credit agreements.

We classify lenders into the following types: bank, bank-affiliated finance company, finance company, investment bank, insurance company, hedge fund, private equity/venture capital, business development company (BDC), and investment manager.[6] In doing so, we rely on lenders' business descriptions in Capital IQ as well as lists of business development companies (from Capital IQ), private equity funds (from Preqin), and hedge funds (from SEC form ADV). If the lender is an individual, a nonfinancial corporation, or a government entity, we

[5] 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.

[6] Investment manager category consists of assets managers that are not primarily in the business of managing hedge funds, private equity, or venture capital funds.

exclude the contract from the sample.[7] Syndicated loans are classified according to the identity of the lead arranger.[8]

We measure borrower characteristics as of the quarter preceding loan origination. For balance sheet variables, we use the most recent quarterly data, while income and cash flow statement items are calculated on a trailing twelve months basis. Borrower financials, as reported in the original filings and thus seen by lenders at the time of loan origination, are from Capital IQ. A detailed description of all variables used in the analysis can be found in Appendix B. All financial ratios are winsorized at the 1st and 99th percentiles. Because our sample includes many relatively small firms, winsorization does not remove all outliers. To deal with this problem, we cap the ratios of debt to assets and research expense to assets as well as sales growth and the level and change in the ratio of EBITDA to assets at a value of one. The final sample consists of 1,227 debt contracts entered into by 561 borrowers. The remaining firms either do not enter raise new debt financing during the 2010-2015 period or borrow through public bond markets.

2.2 Summary statistics

Panel A of Table 1 reports the number of bank and nonbank loans taken out by our sample firms during the 2010-2015 period. We aggregate across multiple tranches within each deal, using the average value of each variable across tranches,[9] and report one observation per deal. Nonbank lenders extend almost one third of all loans in our data.[10] Panel B shows the different types of nonbank lenders in our sample: finance companies (FCOs), bank finance companies (bank FCOs), investment banks, insurance companies, business development companies (BDCs), private equity (PE) and/or venture capital (VC) funds, hedge funds, investment managers, and others.[11] FCOs (23%), PE/VC firms (19%), and hedge funds (16%) account for the largest share of nonbank lending in our sample. Again, an important note to

[7] Nonfinancial lenders primarily represent seller financing and intercompany loans.
[8] The Internet Appendix discusses the results of cluster analysis of lender types.
[9] We use the sum for tranche amounts.
[10] Nonbank deals are on average about half as big as bank deals; therefore, the value-weighted fraction for nonbank loans is 15.5% overall. In 2015, however, even the value-weighted nonbank lending ratio amounts to 27.6%.
[11] Others include collateralized loan obligations, mutual funds and real estate investment trusts.

emphasize from Table 1 is that only 20% of nonbank loans are tracked in DealScan. In particular, DealScan rarely covers loans extended by asset managers.[12]

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, medians, and standard deviations of various firm and loan characteristics for nonbank and bank loans. We test for differences in means and medians between bank and nonbank loans, allowing for unequal variances across the two groups. Since mean and median difference tests yield similar results, our discussion focuses on differences in means.

Nonbank borrowers are significantly smaller than bank borrowers in terms of their book assets and EBITDA. The average nonbank borrower has book assets of $364 million and EBITDA of $30 million. The average bank borrower has book assets of $604 million and EBITDA of $75 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 months EBITDA at loan origination and report the fraction of loans in each bin extended by nonbanks. The fraction of loans originated by nonbanks drops sharply from around 60% to the left of zero EBITDA to 28% to the right of zero EBITDA. We will use this jump later on in our fuzzy regression discontinuity analysis.

Compared to bank borrowers, firms that borrow from nonbanks are younger (28 vs. 37 years), spend a larger fraction of their assets on R&D (9% vs. 5%), and have lower PP&E (0.24 versus 0.27). Nonbank borrowers experience greater stock return volatility (74% vs. 53%).

Along with being smaller, nonbank borrowers get smaller loans ($74 vs. $188 million), but report higher leverage prior to loan origination (36% vs. 26%) than bank borrowers. The interest rate on nonbank loans is 457 basis points higher than the interest rate on bank loans, although the results above suggest that part of this difference is due to nonbank borrowers being riskier. Interestingly, nonbanks loans are less likely to include financial covenants or performance pricing, but they are significantly more likely to use warrants and convertible debt.

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[12] We also checked whether nonbank loans show up as private placements in SDC. The vast majority of nonbank loans in our data are not reported in SDC.

Although mean loan maturity is not significantly different between bank and nonbank loans, median maturity is significantly shorter for nonbank loans.

We next turn to multivariate regression analysis of the characteristics of bank and nonbank borrowers. Table 3 reports estimates from a linear probability model of borrowing from a nonbank lender. Firm size has no effect in any of the five specifications. EBITDA and negative EBITDA in particular are important determinants of whether a firm borrows from a nonbank lender. Consistent with the results in Figure 1, the effect of EBITDA is driven largely by whether a firm has positive EBITDA. While the existing literature shows that less profitable firms are more likely to borrow from finance companies (Carey, Post, and Sharpe (1998)), hedge funds (Agarwal and Meneghetti (2011)), and other nonbank private lenders (Denis and Mihov (2003)), it does not emphasize the importance of positive EBITDA, which in our data is the most important determinant of borrowing from a nonbank lender. The importance of positive EBITDA for bank lending is consistent with banks lacking expertise in maximizing the value of collateral and therefore relying on cash flow as the principal source of loan repayment. Furthermore, banks may be reluctant to extend loans to firms with negative EBITDA because such loans would be rated "substandard" by regulators.[13]

Higher leverage is consistently associated with a significantly higher probability of borrowing from a nonbank lender. A 10% increase in leverage is associated with about 4% increase in the probability of borrowing from a nonbank lender. Firms with higher current ratio are significantly less likely to borrow from a nonbank lender. In column 2, we decompose the current ratio into its major components - cash, receivables, and inventory – and find that the effect works primarily through inventory. A one standard deviation increase of 16% in the ratio of inventory to total assets is associated with 4.5% decline in the probability of borrowing from a nonbank lender.

Column 3 adds controls for the market-to-book ratio, sales growth, volatility, and past returns. Only volatility and past returns are statistically significant, with firms whose stocks experienced higher volatility in the months before loan origination being significantly more

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

likely to borrow from a nonbank lender. Firms that experienced positive buy-and-hold returns prior to loan origination are less likely to borrow from a nonbank lender.

Finally, column 4 and 5 add borrower fixed effects. Although we do not have as much within borrower as cross borrower variation, within borrower variation in profitability, leverage, and volatility has similar effects on the probability of borrowing from a nonbank lender.

3.1 Local banking conditions

How do the conditions in the firm's local banking market affect its decision to borrow from a bank versus nonbank lender? Table 4 reports the results of a linear probability model of the propensity to borrow from a nonbank lender on the characteristics of the county in which borrower's headquarters are located. In column 1 we regress the probability of borrowing from a nonbank lender on the capitalization of banks operating in the firm's county and on the concentration of deposits as a proxy for bank competition. To make sure that the results are not driven by time series trends in bank capitalization and in the propensity to borrow from nonbanks, we include year fixed effects. Identification is therefore based on within-year variation across counties in the capitalization of local banks and in the propensity of local firms to borrow from nonbanks. The coefficient on the bank leverage ratio is negative and statistically significant indicating that when local banks are better capitalized, so that their ratio of tier 1 capital to total assets is larger, firms are less likely to turn to nonbank lenders. This effect is economically meaningful. An increase of 1% in the tier 1 leverage ratio of local banks is associated with a 7.3% decline in the propensity to borrow from a nonbank lender. Relative to the 30% unconditional probability of borrowing from a nonbank lender, this represents a 24% decline.

The coefficient on deposit concentration, which following the existing literature (Petersen and Rajan 1995, Rice and Strahan 2010, Drechsler, Savov, and Schnabl 2017) we use as a proxy for local bank competition, is negative and statistically significant, suggesting that firms located in more competitive banking markets are actually more likely to turn to nonbanks for loan financing. This result is consistent with the predictions of the theoretical model of Donaldson, Piacentino, and Thakor (2017). In their model, firms choose whether to invest in more versus less innovative projects, with the latter having higher expected payoffs but also requiring more monitoring by lenders. Bank competition destroys the incentive of banks to monitor innovative firms, causing such firms to opt for less innovative projects. Nonbank lender's high cost of capital, on the other hand, acts as a commitment device to fund only innovative projects and to monitor. In equilibrium bank and nonbank lenders coexist, with nonbanks lending to more innovative firms. Consistent with the model of Donaldson, Piacentino, and Thakor (2017), the univariate comparisons in Table 2 show that nonbank borrowers are more R&D intensive than bank borrowers. The magnitude of the effect of bank competition is economically meaningful – an increase in deposit concentration of 0.10 is associated with a 3.7% decline in the propensity to borrow from a nonbank lender.[14]

Column 2 of Table 4 controls for industry instead of year fixed effects, while column 3 controls for both industry and year fixed effects.[15] We include industry fixed effects to make sure that the results are not driven by variation across industries in the propensity to borrow from banks (due to, for example, differences in the composition of assets that can be used as collateral) and spatial concentration of industries in certain geographies. For example, it could be that high-tech firms that have few tangible assets are located primarily in wealthier counties that also happen to be more competitive banking markets in which banks have low capitalization ratios due to the presence of many lending opportunities. Controlling for industry fixed effects generates similar results indicating that variation across industries is not driving our results.

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

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[14] An interesting question is how the effect of concentration on nonbank lending varies with the interest rate environment (Drechsler, Savov, and Schnabl 2017). Our sample period is unfortunately too short and does not have enough variation to study this question. The target federal funds rate was 0-25 basis points throughout almost our entire sample period. The target was raised to 25-50 basis points on December 17, 2015.

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

Overall, the results of Table 4 point to county-level drivers of the propensity to borrow from nonbank lenders: capitalization of local banks and competition among them. The first result is consistent with less well-capitalized banks being less willing to extend C&I loans to middle market firms. The second result is consistent with bank competition differentially affecting the ability and willingness of bank and nonbank lenders to screen and monitor innovative firms (Donaldson, Piacentino, and Thakor 2017).

3.2 Which firms borrow from different types of nonbank lenders?

So far we have treated all nonbank loans as being similar, but there could be important differences in the characteristics of firms that borrow from different types of nonbank lenders. To investigate matching between firms and different types of nonbank lenders, Table 5 reports relative risk ratios from multinomial logit regressions predicting lender type. We present the results of three models, with bank loans being the base outcome in all three. Where the models differ is in how they aggregate lender types into larger groups.

In model 1, the four outcomes are 1) borrowing from an independent finance company or a bank-affiliated financed company, 2) borrowing from an investment bank, 3) borrowing from an insurance company, and 4) borrowing from a business development company, private equity, venture capital, hedge fund, or other investment manager. We refer to this last outcome as borrowing from an asset manager. Compared with bank borrowers, firms borrowing from FCOs, investment banks, or asset managers are more likely to have negative EBITDA and higher leverage. Borrowers from asset managers are on average smaller; however, borrowers from investment banks are on average larger than bank borrowers. All nonbanks except for insurance companies lend to firms with higher stock return volatility. Investment banks lend to firms that have experienced favorable stock returns recently, while FCOs and asset managers lend to firms that have had poor stock returns recently. Although a paucity of insurance company loan observations limits statistical power, firms that borrow from insurance companies stand out in having high values of PPE and spending little on R&D. These results are consistent with insurance companies lending to firms with long duration assets in an effort to match the long duration of insurance policies.

Model 2 separates bank FCOs and unaffiliated FCOs, and Model 3 separates hedge funds and investment managers from other types of asset managers.[16] Bank FCOs and unaffiliated FCOs differ in three ways. Negative EBITDA has a large and statistically significant coefficient for unaffiliated FCOs but not for bank FCOs, though the difference between the two coefficients is not statistically significant. Bank FCOs lend to firms with significantly more receivables (Wald test *p*-value for difference in relative risk ratios:: 0.026) than unaffiliated FCOs. Unaffiliated FCOs lend to firms with significantly greater stock return volatility (*p*-value: 0.058) In model 3, we split asset managers into two groups: 1) business development companies, private equity, and venture capital, and 2) hedge funds and investment managers. Model 3 uncovers some interesting differences among these lenders. Highly levered firms are significantly more likely to borrow from hedge funds and investment managers than from business development companies, private equity, or venture capital (Wald test *p*-value for difference in relative risk ratios: 0.049). The latter group is more likely to lend to firms that engage in a lot of R&D (*p*-value: 0.070) and have higher sales growth (*p*-value: 0.046). Firms that borrow from hedge funds and investment managers, on the other hand, do not appear to spend more on R&D than bank borrowers. The difference in R&D intensity between firms that borrow from BDC, PE, and VC firms versus hedge funds could be explained by the former having access to more stable funding and thus having longer investment horizons than hedge funds. BDC and VC firms could also be more skilled in evaluating R&D intensive firms.

4 Differences in contract terms

Univariate comparisons in Table 2 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 less likely to be profitable. The question we ask in this section is whether differences in contract terms persist once we control for firm

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

characteristics. In other words, when firms that are similar on observable characteristics borrow from different types of lenders, do they obtain similar or different terms?

4.1 Interest rate

In Table 6, we present the results of the analysis of the initial interest rate charged on bank versus nonbank loans. Initial interest rate is set to the fixed interest rate for fixed-rate loans and to the current value of the one-month London Interbank Offered Rate (LIBOR) plus the applicable spread for floating-rate loans. Because other loan terms are determined simultaneously with the interest rate, we present the results with and without loan level controls. We include the following firm level controls: log total assets, profitability (EBITDA divided by total assets), leverage, research expense, property, plant & equipment (PP&E), cash, receivables, inventory ratios, and log firm age as well as volatility, past return, growth, and market-to-book ratio in some specifications.

Column 1 presents univariate comparison of the interest rates charged on nonbank versus bank loans. The difference of 444 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 345 basis points. The coefficients on firm characteristics are consistent with theory. Larger and more profitable firms pay significantly lower interest rates. A ten-percentage points reduction in profitability is associated with a 24 basis points higher interest rate. Firms that have lower leverage or more receivables also pay significantly lower interest rates. A ten percentage points decrease in leverage or increase in receivables is associated with 18-26 basis points lower interest rate.

In column 3 we add controls for other loan terms: amount, performance pricing, seniority, security, etc. The coefficient on the nonbank dummy is reduced further from 345 basis points to 216 basis points, suggesting that a large part of the difference in the interest rates charged on bank versus nonbank loans to firms with similar observables is due to differences in the types of loans extended by different lenders. Nonbank loans are significantly more likely to be junior or second lien loans and to charge fixed rates. All of these features are associated with higher interest rates. At the same time nonbank loans are less likely to include performance-pricing provisions, which are associated with lower initial interest rates.

Adding the upfront fee and annual fee in column 4 has little effect on most of the coefficients. The main exception is that the coefficient on performance pricing is reduced by around one third from 56 to 38 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 7-11 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.[17]

In column 5, we control for the volatility of borrowers' stock returns. Besides reducing the coefficient on the nonbank dummy further to 196 basis points, the main effect of controlling for volatility is to reduce the magnitude of the coefficients on warrants, indicating that these are more likely to be included in loans extended to firms with more volatile stock returns.

In columns 6 and 7, we decompose the effect of nonbank lending into different lender types. Controlling for firm and loan characteristics, loans from bank-affiliated finance companies carry 61-66 basis point lower interest rates. Independent finance companies and investment banks charge about 195-274 basis points higher interest rates, while various types of asset managers charge about 433-455 basis points higher interest rates. Finally, in column 8 we include borrower fixed effects to control for time-invariant unobserved heterogeneity. The difference in interest rates between bank loans and nonbank loans increases to 260 basis points.

In unreported analysis, we explore whether simultaneous equity ownership could explain differences in interest rates (Lim, Minton, and Weisbach 2014). Using Capital IQ, we gathered information on each borrower's top 25 holders as of the quarter preceding loan origination. Matching these equity holders with our nonbank lenders, we find that significant equity ownership in borrowing firms by our nonbank lenders is rare. In only 5.79% of the nonbank loans is the lender a blockholder with a 5% or larger stake. Hence these lenders are unlikely to affect the decision on interest rates charged or relationships in general with these borrowers.

4.2 Non-price terms

While we already touched on how differences in non-price terms explain some of the difference in interest rates between bank and nonbank loans, we now turn to a more systematic

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

examination of the non-price terms. Table 7 reports the results of OLS regressions of various non-price terms on lender type dummies. We once again present the results with and without firm controls to show how much of the difference in lending terms is due to matching between firms and lender types.

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

In columns 3 and 4 the dependent variable is maturity. Loans by asset managers have 0.7-1.0 year shorter maturity, but this is entirely due to asset managers lending to small, unprofitable firms. Thus, given their less stable funding, asset managers, hedge funds in particular, lend to firms for which short-term debt is likely to provide more discipline and thus be more optimal than long-term debt. Consistent with insurance companies having very stable funding, loans by insurance companies have almost 6 years longer maturity. This is true even when we control for firm characteristics. The coefficient on profitability, measured as EBITDA/Assets, indicates that a 10% improvement in profitability is associated with about one month longer maturity. Investment banks appear to syndicate longer maturity loans, even controlling for firm size and profitability. Column 5 and 6 indicate that nonbank loans are 12-43% less likely to be senior after controlling for firm characteristics. As shown in column 8, asset managers and insurance companies are less likely to require collateral than banks.

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 convertibility features. With the exception of insurance companies, nonbank loans are significantly less likely to include financial covenants than bank loans. This is especially the case for loans by asset managers, which are 35-48% less likely to include financial covenants. Given that these lenders lend to riskier borrowers, it is somewhat surprising that they do not include financial covenants. It may be the case that nonbank loans are less likely to include financial covenants because these loans are junior to bank loans that do include financial covenants (Park 2000, Rauh and Sufi 2010). However, in unreported analyses, we find very similar effects of lender type dummies on financial covenants when we restrict the sample of loans to senior secured loans and to firms that during our sample period borrow exclusively from banks or nonbanks. Thus even when nonbanks act as senior lenders and do not rely on monitoring by banks, they are less likely to include financial covenants in their credit agreements.

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

Panel B also shows that FCOs, investment banks, and asset managers are about 19-31% less likely than banks to use performance pricing in their loans. For insurance companies, the coefficient is -64%. It is worth noting that financial covenants are almost a necessary condition for performance pricing: less than 3% of all loans with performance pricing do not report having any financial covenants. Also note that fixed rate loans are excluded from this regression since performance pricing is a feature unique to floating rate loans and we address the choice between fixed and floating rates below.

Most nonbanks, except for investment banks and insurance companies, are significantly more likely than banks to use warrants. The use of warrants by finance companies and asset managers is strongly driven by the types of firms they lend to. Adding firm characteristics reduces the size of most coefficients although they remain statistically significant. Most nonbanks also use convertible debt more frequently, although we do not find any loans with a convertibility feature made by bank FCOs or insurance companies.

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

Turning to the upfront fees in columns 3 and 4, finance companies, investment banks, and hedge funds charge 37, 47 and 33 basis points higher upfront fees. About one third of the effect for finance companies is explained by the characteristics of firms they lend to; controlling for size in particular reduces the coefficient on the finance company dummy from 37 to 24 basis points and reduces its statistical significance. The coefficient on investment banks is only marginally affected by adding firm controls while the coefficient on hedge funds drops from 33 to 8 basis points and loses its significance. There are no significant differences in terms of the propensity of different lender types to charge annual fees. It is worth noting though that only 7% of sample loan contracts contain an annual fee. Finally, almost all nonbank lenders except for insurance companies are marginally more likely than banks to make loans secured by a second lien.

4.3 Fuzzy regression discontinuity design (RDD) around zero EBITDA

While the analyses in Tables 6 and 7 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 regulatory constraints on banks' ability to lend to negative cash flow borrowers.

The OCC Comptroller's Handbook on Rating Credit Risk (2001) provides guidance on how banks should design their internal credit risk rating systems. Although banks have considerable leeway over the design of their rating system for credits that do not attract special regulatory scrutiny, the handbook spells out clear definitions of "nonpass" credits, which banks are expected to adhere to regardless of what rating system they otherwise use. According to these definitions, loans to unprofitable firms are to be adversely classified as "substandard". Such loans trigger additional regulatory reporting and loan loss reserve requirements.

In addition, 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. These regulatory constraints also help alleviate concerns on banks and nonbanks potentially relying on different unobservable characteristics of borrowers (e.g., lending relationships). 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 A4 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 30-37% 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. We do not find any consistently significant jump in any other covariate except for cash holdings, which are arguably driven by cash flows. Importantly, among bank borrowers we do not find a discontinuity in the propensity to borrow from a relationship bank.

A common concern with regression discontinuity designs is the possibility that firms could manipulate the running variable, in our case EBITDA, which determines assignment to treatment. Note however that what is important for identification is not whether agents have some control over the running variable but whether they can *precisely* manipulate it (Lee and Lemieux 2010). As long as firms cannot precisely manipulate their EBITDA, assignment to treatment is locally randomized around zero EBITDA (Lee and Lemieux 2010). To alleviate the concern that firms may be able to precisely manipulate their EBITDA, Figure 2 shows the histogram of EBITDA with a bin width of \$1 million. The mode of EBITDA is just below zero, with fewer observations just above zero, contrary to what one would expect if firms were manipulating their EBITDA. Visually, the distribution appears smooth around zero. In the Internet Appendix, we use local polynomial density estimation following Cattaneo, Jansson, and Ma (2017) to formally test for a discontinuity in the EBITDA distribution. The test fails to reject the null hypothesis that the distribution is smooth.

Having shown that zero EBITDA allows us to utilize a fuzzy regression discontinuity design, we now present the results for the causal effect of borrowing from a nonbank lender on various loan terms using zero EBITDA as an instrument for nonbank lending. Table 8 uses the nonparametric estimation methodology of Calonico, Cattaneo, and Titiunik (2014) to estimate treatment effects. The optimal neighborhood bandwidth is chosen using the coverage error-rate (CER)-optimal bandwidth selector (Calonico, Cattaneo, and Farrell, 2017), which is more conservative than traditional mean squared error bandwidth selectors. Because the bandwidth selector uses the structure of all the data, it needs to be re-estimated for each outcome variable. Internet appendix Table A6 shows that the results are robust to using ad-hoc neighborhoods around zero EBITDA. The optimal bandwidth around zero EBITDA for the initial interest rate as the outcome variable is [-32.5, 32.5]. In the second stage, we find an interest rate differential of 565 basis points with a z statistic of 4.10. 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.

Nonbank loans are 58 percentage points less likely to include financial covenants and 42 percentage points more likely to include warrants. These differences are again somewhat larger than the ones in the OLS regressions of Table 6. Although statistically significant only at the 10% level, there is some evidence that nonbank loans have shorter maturity (2.4 years) and carry higher fees.

Table 8 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.

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

4.4 Matching results

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

Imbens and Rubin (2015) suggest using mean differences normalized by the standard deviation and the variance ratios to examine covariate balance. In Panel A of Table 9, we provide these statistics for the 'raw' and matched sample for matching conducted for the first column of Panel B, where we report matching results for the interest rate on the loan. The raw sample is the sample of treated and non-treated observations before matching is performed.

The first two columns in Panel A report differences in means that are standardized by the subsample standard deviations. A well-balanced sample would have these values close to zero. Statistics for the raw sample suggest that there is little balance in the borrower size, profitability, or leverage. After matching, the balance improves significantly with the difference of means approaching zero. The last two columns in Panel B provide variance ratios for the two subsamples. A well-balanced sample would have these values close to one. Statistics for the raw sample again suggest that there is little balance for firm size, profitability, and leverage in addition to some other firm level variables such as research expense, cash, and inventories. The matched sample, however, is much better balanced with the variance ratio dropping to 1-1.5 for firm size, profitability, leverage and other variables. These statistics suggest that the matched sample is better balanced than the raw sample and is well balanced in most, if not all, dimensions.

We present the average treatment effect on the treated (ATET) with Abadie-Imbens (AI) robust standard errors in Panel B of Table 9. We adjust the Mahalanobis estimate for bias from matching on continuous variables using the firm-level control variables introduced earlier. The estimated ATET for the initial interest rate on the loan is positive with a coefficient of 334 basis points, statistically significant at the 1% level. ATET for loan size is negative and also significant at the 1% level, as presented in column 2. Estimated effect on seniority, security, and financial covenants are also negative with statistically significant coefficients at the 1% level. As expected, ATET for warrants is estimated to be positive (15%) and again statistically significant. These results provide strong evidence that, compared with banks, nonbank lenders charge significantly higher interest rates, are less likely to require collateral or financial covenants but are more likely to include warrants.

5 Performance of bank and nonbank borrowers

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

5.1 Future performance of nonbank borrowers

We start by asking whether nonbank borrowers are more likely to file for bankruptcy than bank borrowers. If banks are better at monitoring their borrowers, in part through inclusion of financial covenants in their loan agreements, then banks may step in and fix any problems earlier, thereby reducing the probability that their borrowers are forced to file for bankruptcy. We collect bankruptcy dates, as of May 2018, from Capital IQ. In our sample, there are 53 deals by 32 borrowers that end in bankruptcy within three years after loan origination. Relative to the number of deals originated from January 2010 through May 2015, this corresponds to 4.6% probability of bankruptcy. As a point of reference, over the 1970-2015 period the three-year cumulative default rate for BB rated bonds was 4.5% (Moody's 2016).

Table 10 reports estimates from a linear probability model of bankruptcy over the three years following loan origination. In column 1, we include only the nonbank dummy, our main explanatory variable of interest. The marginal effect is a 4.1% increase in the probability of bankruptcy. As we add firm size and profitability in column 2, the effect of nonbank lender declines to 3.2%. As expected, profitability is negatively correlated with bankruptcy. As we control for additional firm characteristics in column 3, the effect of nonbank lender is reduced further and loses its statistical significance. Column 4 controls for market-to-book, sales growth, volatility, and past stock returns. More volatile firms and firms that experience lower stock returns prior to loan origination are significantly more likely to file for bankruptcy. Overall, controlling for the full set of firm characteristics, the coefficient on the nonbank dummy is small and not significant.

Because bankruptcy is an extreme outcome, the analysis in Table 10 may not have enough statistical power to pick up smaller changes in operating performance. Table 11 therefore looks at year-to-year changes in profitability. The limitation of the analysis in Table 11 is that we can measure changes in profitability only for firms that survive and remain public for long enough after loan origination. 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 the nonbank lender dummy is negative and significant only in the first column, where we study the change in the profitability over the first year after the loan is extended. This coefficient loses its significance in column 4, once we include firm volatility, sales growth, market-to-book as controls. Furthermore, analyzing changes in the second and third years after loan origination, we find that the coefficient on the nonbank dummy is not statistically different from zero in any specification. Together with the bankruptcy analysis in Table 10, these results indicate that conditional on firm characteristics, bank and nonbank borrowers perform similarly following loan origination. In the Internet Appendix, we assess future profitability for various nonbank lenders separately and also perform similar tests using subsequent stock returns (including delisting returns) to alleviate concerns about survivorship bias in the accounting data. Again, we do not find evidence for underperformance beyond the first year and even the first-year evidence is not consistent across measures. PE/VC/BDC borrowers show temporary stock return underperformance during the first year after loan origination, but do not exhibit cash flow underperformance. FCO and insurance borrowers have lower cash flows in the first year in some specifications, but do not underperform in terms of stock returns.

To summarize, we do not find any evidence that borrowers from nonbank lenders are doing worse than bank borrowers in terms of future profitability or the probability of bankruptcy. These findings are important in that they suggest that the nonbank lending market is not yet competitive. Although it is not statistically significant, the coefficient of 0.012 in column 4 of Table 10 indicates that nonbank loans have a 1.2% higher probability of filing for bankruptcy within three years of loan origination. Assuming a recovery value of 50% for defaulted loans, expected losses for nonbank lenders are about 0.2% annually. Given that nonbanks charge an interest rate that is about 2% higher than bank rates, nonbank lenders appear to earn high returns even after accounting for loan losses.

5.2 Announcement returns for nonbank borrowers

Our analysis of the non-price terms in Table 7 shows that loans from nonbank lenders are significantly less likely to include financial covenants, suggesting that nonbank lenders may engage in less on-going monitoring after loans are originated. Do nonbank lenders engage instead in more ex ante screening of the borrowers they lend to? Nonbank lenders such as hedge funds and other asset managers may have a comparative advantage in identifying good investment opportunities. And the type of unprofitable, R&D intensive firms that these lenders provide funding to may require more ex ante screening than older, more established firms that are already profitable. Lenders to the latter just need to make sure that performance does not deteriorate and that if it does they can step in. If nonbank lenders do engage in more ex ante screening than bank lenders, we may expect nonbank borrowers to experience larger announcement returns around loan origination.[18]

In Table 12 we analyze announcement returns around origination of bank versus nonbank loans. In columns 1-3 we calculate cumulative abnormal returns from loan origination through the day on which an 8-K SEC filing discloses the terms of the new loan; in columns 4-6 we calculate abnormal returns on the announcement date itself.[19] We focus on the returns between

[18] We acknowledge that an abnormal positive stock price reaction to a nonbank loan would also be observed if the alternative for the borrower is no funding leading to severe financial constraints. However, we believe that this possibility is less likely for our sample firms since they are all publicly-traded and there is no evidence that announcement returns are related to negative cash flows as discussed below.

[19] Abnormal returns are calculated based on the market model estimated using daily returns over the year ending 20 calendar days prior to loan origination. We require at least 120 daily return observations to estimate market beta.

loan origination and filing date (columns 1-3) because Ben-Rephael et al (2018) show that most price discovery takes place around the event rather than filing date.

The sample is limited to loans for which the filing occurs within five calendar days of loan origination and for which the last stock price before origination is at least $1. Column 1 regresses CARs on the nonbank dummy. The constant term indicates that bank loan announcement returns do not differ from zero on average. The coefficient on the nonbank dummy is positive and statistically significant. It indicates that nonbank loans experience announcement returns that are 3.3% higher than announcement returns for bank loans.

One concern with the univariate results in column 1 is that the coefficient on the nonbank dummy may be driven by returns experienced by unprofitable firms that are able to secure debt financing. In column 2, we control for negative EBITDA, firm size, and leverage. Neither coefficient is statistically significant, and their inclusion does not affect the coefficient on the nonbank dummy. In column 3, we control for loan characteristics such as the presence of financial covenants, warrants, as well as the loan's maturity. The coefficient on the nonbank dummy is reduced from 3.3% to 2.9%, but it retains statistical significance, while none of the controls are statistically significant.

Columns 4-6 show abnormal returns only on the announcement date itself. Again, we do not find evidence of positive announcement returns for bank loans. In the univariate setting, nonbank loan announcement returns are 1.5% higher than those for bank loans. When controlling for firm and loan characteristics, the return difference remains similar at 1.3% though it loses statistical significance. These results are consistent with at least some market participants becoming aware of the successful closing of a loan before the 8-K is filed (Ben-Rephael et al (2018))

Our results that nonbank loans experience larger announcement returns than bank loans differ from James (1987) who finds that during the 1974-1983 period bank loans experience positive announcement returns while private placements are if anything associated with negative returns. Preece and Mullineaux (1994) on the other hand find a positive stock price reaction to loans by nonbank lenders. Billett, Flannery, and Garfinkel (1995) also find average returns for private placements that are actually larger than returns for bank loans but that are not statistically significant, perhaps due to the small number of private placements in the data. The composition of our nonbank loan sample is very different from these papers. In their samples, the majority of nonbank loans involve private placements with insurance companies. Our sample of nonbank loans has relatively few insurance companies and is instead dominated by finance companies, hedge funds, private equity, and venture capital firms. In our data, insurance companies lend to firms with more PPE and are as likely as banks to include financial covenants in their loans. Thus, it may be that because they rely on the value of the real estate collateral backing their loans and on financial covenants to catch deterioration in borrower's financial conditions, insurance companies do not engage in as much ex-ante screening as other nonbank lenders. In fact, in an unreported regression, we find that loans from insurance companies are associated with 2.9% lower announcement returns than loans from other nonbanks, and this result is statistically significant at the 5% level.

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

6 Conclusion

We present novel systematic evidence on the terms of direct lending by nonbank financial intermediaries to publicly-traded middle market firms during the post crisis period. Such lending is widespread with about one third of all loans in our data being extended by nonbanks. Smaller, unprofitable, R&D-intensive firms with high stock volatility are significantly more likely to borrow from nonbanks. Firms located in counties with less well-capitalized banks and in less concentrated banking markets are more likely to turn to nonbank lenders for debt financing.

Consistent with the existence of market segmentation, nonbank loans carry significantly higher interest rates. Controlling for firm characteristics and other loan terms, the average difference in interest rates is around 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 565 basis points. Higher interest rates charged on nonbank loans do not appear to be compensation for risk as, controlling for firm characteristics, nonbank borrowers file for bankruptcy at similar rates as bank borrowers and experience similar operating performance following loan origination.

Matching between borrowers and lenders appears to be driven by lenders trying to match the maturity of their loans with the effective maturity of their funding. In particular, insurance companies lend at very long maturities, while hedge funds lend at short maturities. Lenders match with borrowers for which long versus short maturity loans are likely to be optimal (Diamond (1991b)).

Finally, different lender types appear to use different lending techniques. Nonbank lenders are significantly less likely than banks to include financial covenants or performance pricing provisions in their loans. Thus, rather than relying on financial covenants to monitor borrowers' ex-post performance, nonbank lenders engage in extensive ex-ante screening. Consistent with this idea, we find large positive abnormal returns around announcements of nonbank loans.

Appendix A. Details on sample construction

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

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

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

Loan amendments are not necessarily filed as exhibits, but might simply be described in a short paragraph in a company's 10-Q or 10-K filing and are thus much more difficult to track consistently than contracts that are stated in full. Since this paper focuses on sources of funds and initial contract terms rather than renegotiations, we drop all simple amendments and retain only original debt contracts as well as amended and restated debt contracts, which presumably represent more substantial changes. We also exclude promissory notes that are issued pursuant to an existing credit agreement, such as notes evidencing a drawdown of a line of credit. Finally, we drop 14 debtor-in-possession credit agreements.

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

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

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

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

Appendix B. Variable definitions

Variable	Definition	Source
Loan characteristics		
Annual fee	Fee the borrower has to pay to lender annually, expressed in basis points of the entire commitment.	Manual collection, DealScan
Convertible	Indicator equals one if the debt is convertible, zero otherwise	Manual collection
Financial covenants	Indicator equals one if the debt contract contains any financial covenants, zero otherwise	Manual collection, DealScan
Fixed rate loan	Indicator equals one if debt is fixed rate, zero if debt is floating rate	Manual collection, DealScan
Initial interest rate	Equals fixed rate for fixed rate debt, level of 1-month LIBOR (adjusted for interest rate floors) at origination plus spread for floating rate debt	LIBOR levels obtained from Federal Reserve Bank of St. Louis FRED database
Loan size	Total size of the commitment	Manual collection, DealScan
Ln(amount)	Natural log of loan size	Manual collection, DealScan
Maturity	Maturity of the debt expressed in years	Manual collection, DealScan
Nonbank	Indicator equals one if the lender is a nonbank, zero otherwise	Capital IQ, Preqin, 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 debt is senior, zero otherwise	Manual collection, DealScan
Upfront fee	Fee the borrower has to pay to lender at origination, expressed in basis points of the entire commitment	Manual collection, DealScan
Warrants	Indicator equals one if the lender receives warrants in conjunction with the debt issue, zero otherwise	Manual collection, DealScan
Firm characteristics		
Cash	Cash and cash equivalents divided by total assets.	Capital IQ
Current ratio	Current assets divided by current liabilities.	Capital IQ
Coverage ratio	EBITDA divided by interest expense.	Capital IQ
EBITDA	Earnings before interest, taxes, depreciation and	Capital IQ

	amortization (EBITDA).	
EBITDA < 0	Indicator equals one if EBITDA is negative, zero otherwise.	Capital IQ
Firm age	Number of years since the firm was founded.	Capital IQ, 10-K
Inventory	Inventory divided by total assets.	Capital IQ
Leverage	Long-term debt plus debt in current liabilities divided by total assets.	Capital IQ
Market-to-book	Common shares outstanding times stock price plus preferred stock plus long-term debt plus debt in current liabilities, divided by total assets	Capital IQ
Profitability	Ratio of EBITDA to total assets.	Capital IQ
Δ Profitability	Annual change in the ratio of EBITDA to total assets.	Capital IQ
Receivables	Receivables divided by total assets.	Capital IQ
Research expense	Research expense divided by sales.	Capital IQ
Sales growth	Sales in year *t* divided by sales in year *t*-1 minus one	Capital IQ
PP&E	Net property, plant and equipment scaled by total assets.	Capital IQ
Total Assets	Total book assets.	Capital IQ
Volatility	Standard deviation of daily stock returns measured over 180 calendar days ending 20 days prior to loan origination, multiplied by the square root of 252. We supplement CRSP with daily stock returns from OTC Markets and Capital IQ.	CRSP, OTC Markets, Capital IQ
Past return	Buy-and-hold stock return measured over 180 calendar days ending 20 days prior to loan origination. We supplement CRSP with daily stock returns from OTC Markets and Capital IQ.	CRSP, OTC Markets, Capital IQ
County characteristics		
Bank leverage ratio	Deposit-weighted average of the tier 1 leverage ratio of bank holding companies with branches in the county of the firm's headquarters.	Summary of Deposits, Y9-C
Deposit concentration	Herfindahl-Hirschman Index of bank deposit concentration in the county of the firm's headquarters. Deposit shares within a county are aggregated across multiple banks owned by the same bank holding company. Deposits are reported as of June of the year prior to loan origination.	Summary of Deposits

Ln(Total deposits)	Natural logarithm of the aggregate value of deposits in the county of the firm's headquarters.	Summary of Deposits
Ln(Personal income)	Natural logarithm of the per capita personal income in the county of the firm's headquarters.	BEA Regional Economic Accounts
Unemployment rate	Unemployment rate in the county of the firm's headquarters.	BLS Local Area Unemployment Statistics

The following variables are winsorized at the 1st and 99th percentile: leverage, current ratio, coverage ratio, PP&E, cash, receivables, inventory, market-to-book, research expense, sales growth, and past return. Volatility is winsorized at the 5th and 95th percentile due to a large number of outliers in the right tail. In addition, the leverage, sales growth, research expense, profitability, and Δ profitability measures are capped at a maximum value of one and the minimum value for profitability and Δ profitability is set to minus one to eliminate outliers that persist after winsorization.

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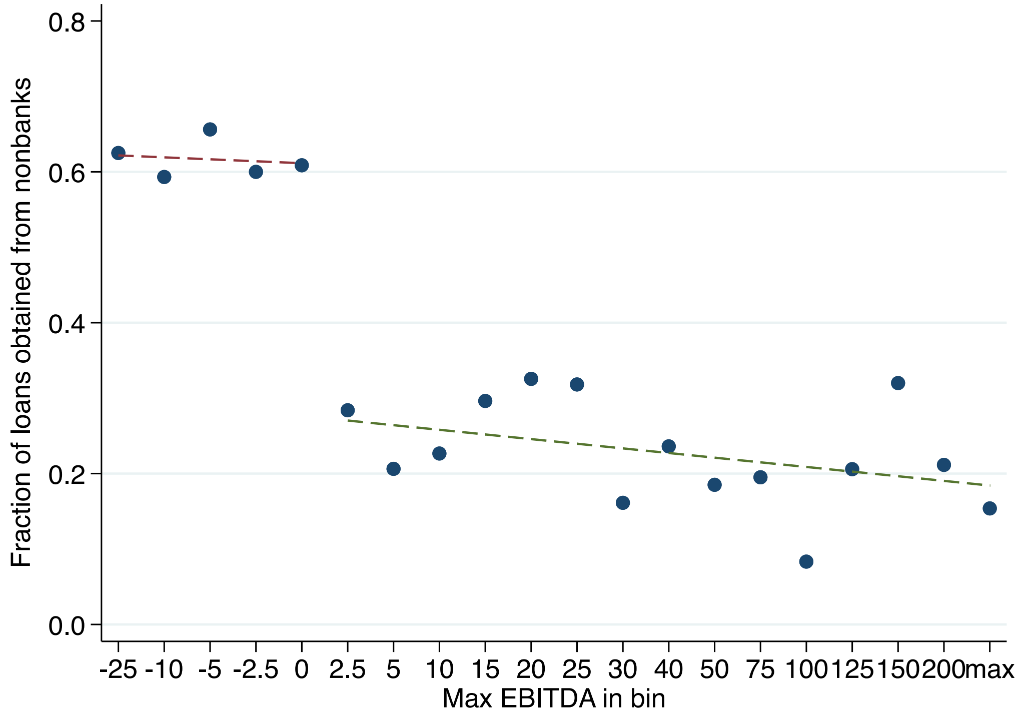

Figure 1: Fraction of loans obtained from nonbanks by EBITDA bin

This figure shows the fraction of loans obtained from nonbanks at different levels of EBITDA. Loans are allocated into twenty bins based on borrower's trailing twelve months EBITDA at loan origination. The x-axis shows the upper limit of EBITDA for each bin. The choice of bin limits roughly follows the distribution obtained by splitting EBITDA into twenty quantiles, rounded to multiples of five.

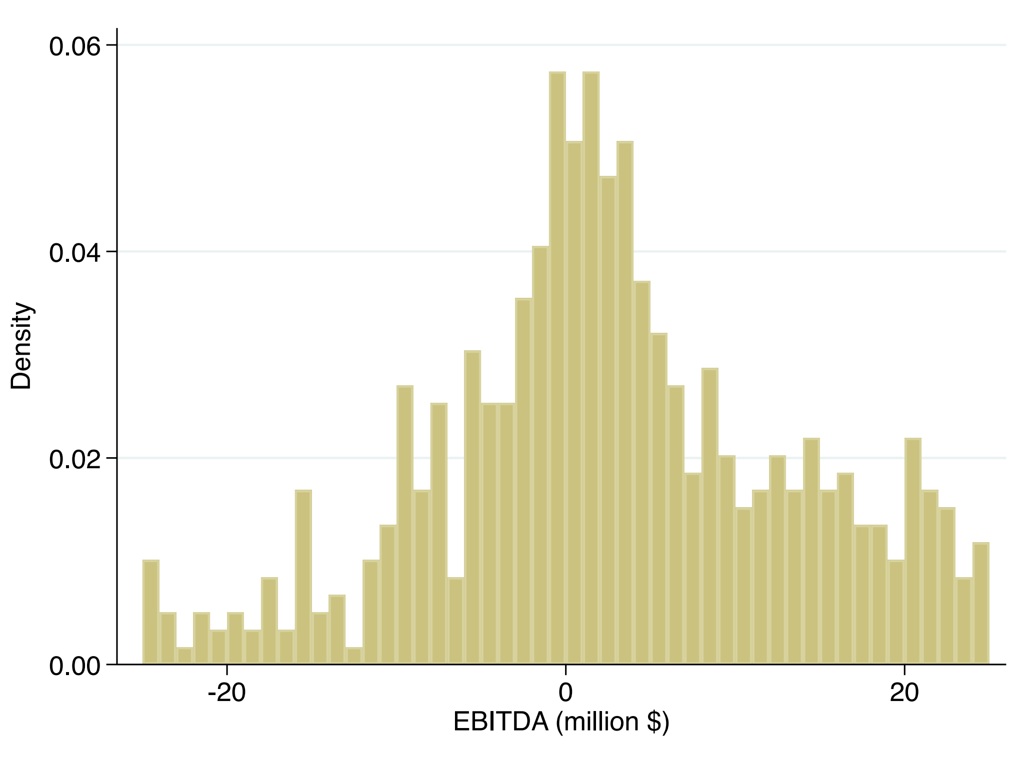

Figure 2: Histogram of trailing twelve months EBITDA
This figure shows the histogram of trailing twelve months EBITDA for borrowers with EBITDA in the -$25 million to $25 million range. Bin width is one million dollars. The sample includes all borrowings of a random sample of 750 middle-market firms originated and filed with the SEC during the 2010-2015 period.

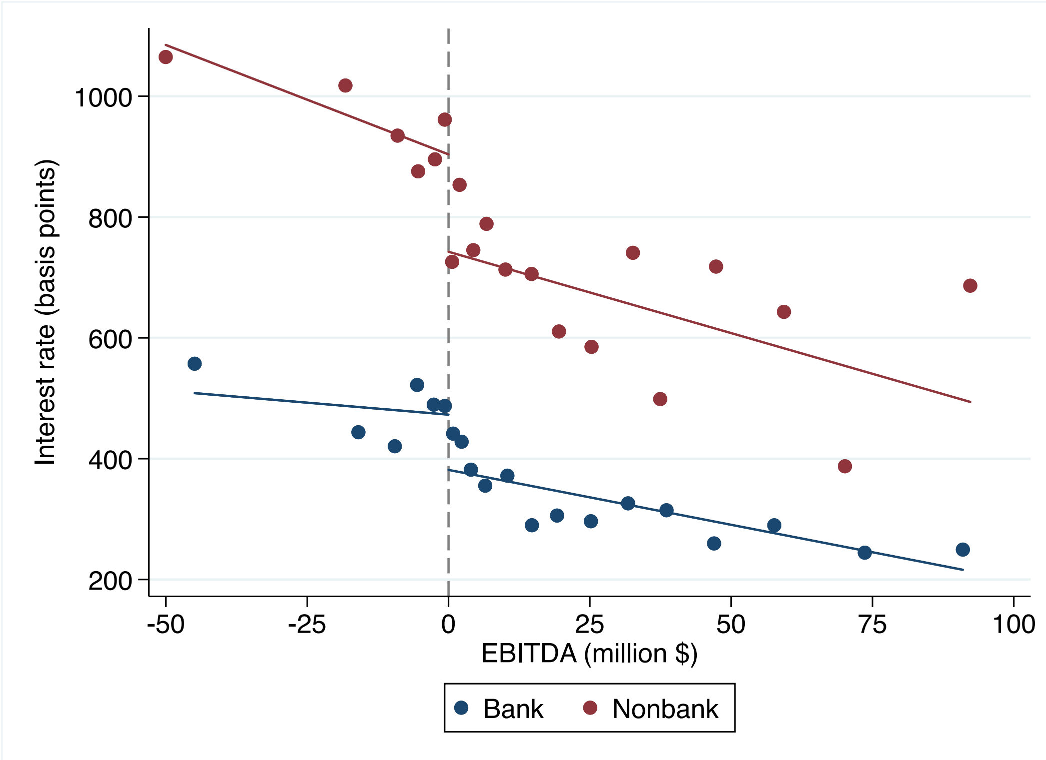

Figure 3: Relation between interest rate and EBITDA
This figure shows the interest rate charged on bank versus nonbank loans at different levels of borrower's EBITDA. Loans are allocated into twenty quantiles based on trailing twelve months EBITDA at loan origination. The figure includes loans of borrowers with EBITDA between -$100 million and $100 million.

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

Panel A reports for each year the total number of loans originated and the share extended by nonbanks. Panel B reports for each nonbank lender type, the number loans originated and the percentage included in the DealScan database. The sample includes all borrowings of a random sample of 750 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	219	31.05
2011	261	30.27
2012	233	33.05
2013	195	34.36
2014	201	29.35
2015	118	33.90
Total observations	1,227	31.78

Panel B: Lender types and DealScan match rates

	Obs.	% of nonbank deals	% tracked in DealScan
Bank	837		54.00
Nonbanks:			
Bank FCO	51	13.08	27.45
FCO	89	22.82	26.97
Investment bank	39	10.00	76.92
Insurance	22	5.64	4.55
BDC	15	3.85	13.33
PE/VC	74	18.97	0.00
Hedge fund	62	15.90	6.45
Investment manager	33	8.46	6.06
Other	5	1.28	20.00
Total observations	390	100.00	20.00

Table 2: Summary statistics for bank vs. nonbank loans

This table reports firm and loan characteristics for bank and nonbank loans. The sample includes all non-bond borrowings of a random sample of 750 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level using the average value of each variable across tranches in a deal. Variable definitions are in Appendix B. *, **, and *** indicate statistical significance for differences between bank loans and nonbank loans at 10%, 5%, and 1%. Statistical significance for differences in means is assessed using *t*-tests that allow for unequal variances across groups. Statistical significance for differences in medians is assessed using the Wilcoxon rank-sum test.

	Nonbank loans				Bank loans			
	Obs.	Mean	Median	St.dev.	Obs.	Mean	Median	St.dev.
Total assets	372	364.31	135.53	700.12	813	603.65***	308.54***	1033.36
EBITDA	376	30.00	1.73	100.36	811	74.88***	31.72***	159.29
Profitability	371	-0.09	0.02	0.31	809	0.09***	0.11***	0.17
Leverage	372	0.36	0.29	0.28	813	0.26***	0.21***	0.22
Market-to-book	345	1.62	1.14	1.36	771	1.56	1.19	1.15
Research expense	372	0.09	0.00	0.19	813	0.05***	0.00***	0.10
PP&E	370	0.24	0.16	0.24	806	0.27**	0.19**	0.26
Cash	372	0.13	0.06	0.16	813	0.12	0.08	0.14
Receivables	372	0.17	0.14	0.14	813	0.15**	0.13*	0.12
Inventory	372	0.12	0.05	0.15	813	0.13	0.07	0.17
Firm age	390	27.58	20.00	26.29	837	37.34***	27.00***	32.64
Sales growth	344	0.15	0.07	0.38	779	0.14	0.07	0.30
Volatility	350	0.74	0.64	0.38	781	0.53***	0.45***	0.27
Past return	350	-0.09	-0.06	0.47	781	0.05***	0.06***	0.34
Deal size	389	74.36	22.00	183.68	836	188.44***	75.00***	337.07
Maturity	387	4.03	3.66	2.56	822	3.98	4.51	1.91
Fixed rate loan	383	0.56	1.00	0.49	814	0.04***	0.00***	0.19
Initial interest rate (bps)	376	784.21	800.00	383.76	769	327.24***	290.28***	165.99
Senior	390	0.74	1.00	0.44	836	0.98***	1.00***	0.14
Second lien	390	0.04	0.00	0.20	837	0.01***	0.00***	0.07
Secured	387	0.81	1.00	0.39	801	0.86**	1.00**	0.34
Performance pricing	390	0.05	0.00	0.22	837	0.37***	0.00***	0.47
Upfront fee (bps)	319	43.18	0.00	85.57	730	17.10***	0.00***	40.32
Annual fee (bps)	318	4.66	0.00	29.61	733	2.69	0.00	12.08
Financial covenants	390	0.50	0.58	0.50	837	0.87***	1.00***	0.33
Warrants	390	0.24	0.00	0.43	836	0.02***	0.00***	0.14
Convertible	390	0.15	0.00	0.36	836	0.00***	0.00***	0.05

Table 3: Probability of borrowing from a nonbank lender

This table reports the results from linear probability models of whether a loan is extended by a nonbank lender. The sample includes all non-bond borrowings of a random sample of 750 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level using the average value of each variable across the tranches in a deal. Industry fixed effects are based on Fama-French 12 industries. *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)
Ln(Assets)	-0.00	-0.01	0.01	-0.02	-0.03
	(-0.31)	(-0.62)	(0.65)	(-0.35)	(-0.43)
EBITDA	-0.00	-0.00	-0.00	-0.00	-0.00
	(-1.43)	(-1.45)	(-1.20)	(-0.51)	(-0.25)
EBITDA < 0	0.33***	0.35***	0.28***	0.23***	0.19*
	(7.48)	(8.26)	(6.06)	(2.63)	(1.90)
Leverage	0.33***	0.38***	0.33***	0.30**	0.23
	(4.53)	(5.78)	(4.61)	(2.17)	(1.48)
Research expense	-0.01	0.00	0.12	-0.05	0.15
	(-0.07)	(0.01)	(0.89)	(-0.12)	(0.27)
PP&E	-0.07	-0.05	-0.03	0.09	0.09
	(-0.76)	(-0.53)	(-0.38)	(0.29)	(0.26)
Current ratio	-0.03***				
	(-2.66)				
Cash		-0.12	-0.12	-0.14	-0.02
		(-0.93)	(-0.84)	(-0.47)	(-0.06)
Receivables		0.22	0.24	0.20	0.32
		(1.04)	(1.04)	(0.42)	(0.60)
Inventory		-0.28**	-0.23*	0.59	0.73
		(-2.57)	(-1.85)	(1.14)	(1.32)
Ln(Firm age)	-0.02	-0.02	-0.01	-0.26	-0.30
	(-0.99)	(-0.66)	(-0.27)	(-1.45)	(-1.31)
Market-to-book			-0.01		-0.04
			(-0.78)		(-1.34)
Sales growth			0.07		-0.04
			(1.64)		(-0.34)
Volatility			0.21***		0.21*
			(3.48)		(1.79)
Past return			-0.11***		-0.08
			(-3.00)		(-1.37)
Constant	0.26**	0.19*	-0.06	0.99	1.11
	(2.58)	(1.73)	(-0.45)	(1.12)	(1.00)
Year effects	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	No	No
Borrower effects	No	No	No	Yes	Yes
Observations	1171	1171	1090	1171	1090

Table 4: Local banking markets and propensity to borrow from nonbanks

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank leverage	-0.073***	-0.059***	-0.074***	-0.061***	-0.070***	-0.075***	-0.072***	-0.058***
	(3.25)	(2.87)	(3.47)	(2.81)	(3.47)	(3.87)	(3.73)	(2.64)
Deposit concentration	-0.369***	-0.264*	-0.292**	-0.321***	-0.287**	-0.292**	-0.289**	-0.302**
	(2.79)	(1.93)	(2.17)	(2.58)	(2.38)	(2.42)	(2.39)	(2.37)
Ln(Total deposits)				0.013				0.009
				(1.20)				(0.74)
Ln(Per capita personal income)					0.034			0.043
					(0.67)			(0.71)
Personal income growth						-0.190		-0.226
						(-0.43)		(-0.50)
Unemployment rate							0.006	0.008
							(0.77)	(0.91)
Year effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,200	1,200	1,200	1,200	1,200	1,200	1,200	1,200

Table 5: 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. Bank loans are the base outcome in all models. Model 1 aggregates nonbank lenders into 1) finance companies (FCOs) and bank-affiliated FCOs; 2) investment banks; 3) asset managers; and 4) insurance companies. Model 2 splits FCOs into bank-affiliated versus unaffiliated ones. Model 3 splits assets managers into BDC/PE/VC versus hedge fund/investment manager. For models 2 and 3, the full model is estimated, but only results for the labeled categories are tabulated. Year and Fama-French 12 industry fixed effects are included in all specifications. z-statistics adjusted for clustering by firm are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Total number of observations is 1,085.

	Model 1				Model 2		Model 3	
	FCO / Bank FCO	Investment bank	Asset managers	Insurance	Bank FCO	Unaffiliated FCO	BDC / PE / VC	Hedge fund / IM
Ln(Assets)	1.26	2.30***	0.86	1.19	1.25	1.20	0.84	0.89
	(1.62)	(2.93)	(-1.08)	(0.37)	(0.96)	(1.20)	(-1.04)	(-0.62)
EBITDA	1.00*	1.00	0.99**	1.00	1.00	0.99***	0.99	0.99**
	(-1.75)	(-0.77)	(-2.47)	(-0.11)	(-0.91)	(-2.60)	(-1.61)	(-2.32)
EBITDA < 0	2.08**	3.82**	4.84***	6.51*	1.11	2.64**	4.45***	5.61***
	(2.19)	(2.10)	(5.14)	(1.92)	(0.16)	(2.43)	(3.58)	(4.31)
Leverage	5.35***	4.17	12.22***	1.29	5.18*	6.06***	5.42**	18.85***
	(2.74)	(1.49)	(4.26)	(0.15)	(1.77)	(2.77)	(2.30)	(4.73)
Research expense	1.78	0.00	3.18	0.00	0.14	1.59	10.87**	0.48
	(0.42)	(-1.56)	(1.12)	(-1.33)	(-0.56)	(0.28)	(2.13)	(-0.46)
PP&E	0.67	0.80	0.52	10.71	2.06	0.30	0.64	0.49
	(-0.53)	(-0.21)	(-0.87)	(1.59)	(0.65)	(-1.49)	(-0.54)	(-0.70)
Cash	1.38	5.13	0.11**	0.03	0.51	1.09	0.23	0.04**
	(0.26)	(0.99)	(-2.19)	(-1.34)	(-0.31)	(0.07)	(-1.38)	(-2.17)
Receivables	8.61	1.60	2.62	0.46	142.07**	0.70	5.48	1.29
	(1.18)	(0.18)	(0.75)	(-0.21)	(2.07)	(-0.27)	(1.09)	(0.17)
Inventory	0.30	0.09	0.20	0.81	0.81	0.15**	0.15	0.22
	(-1.34)	(-1.22)	(-1.45)	(-0.11)	(-0.15)	(-2.18)	(-1.49)	(-1.14)
Ln(Firm age)	0.88	0.91	0.92	1.30	0.62	1.26	1.03	0.88
	(-0.50)	(-0.31)	(-0.41)	(1.09)	(-1.61)	(1.09)	(0.11)	(-0.64)
Market-to-book	0.78*	0.91	0.99	1.15	0.54*	0.86	1.00	0.96
	(-1.69)	(-0.34)	(-0.06)	(0.69)	(-1.76)	(-0.90)	(-0.02)	(-0.31)
Sales growth	0.84	1.93	2.49**	0.50	1.23	0.71	4.22***	1.68
	(-0.49)	(1.07)	(2.49)	(-0.65)	(0.37)	(-0.78)	(3.40)	(1.19)
Volatility	2.84**	5.09**	3.16***	0.17	0.71	5.00***	2.75	3.26***
	(2.29)	(2.09)	(2.84)	(-0.69)	(-0.41)	(2.81)	(1.36)	(2.70)
Past return	0.46**	2.17*	0.40***	1.76	0.69	0.37***	0.36**	0.46***
	(-2.49)	(1.69)	(-3.33)	(0.62)	(-0.73)	(-2.98)	(-2.21)	(-2.70)
Non-zero obs. in category	119	34	153	21	47	72	65	88

Table 6: Initial interest rate charged on bank versus nonbank loans

This table reports the results of regressions of the initial interest rate 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 750 middle-market firms originated during the 2010-2015 period. Variable definitions are in Appendix B. Industry fixed effects are based on Fama-French 12 industries. *t*-statistics adjusted for firm-level clustering are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nonbank	444.37***	345.00***	216.39***	208.29***	195.90***			260.23***
	(13.83)	(13.01)	(8.32)	(6.59)	(7.70)			(4.66)
Bank FCO						-61.29**	-65.97***	
						(-2.28)	(-2.66)	
FCO						273.99***	250.64***	
						(6.89)	(6.46)	
Investment Bank						194.42***	195.30***	
						(5.53)	(5.28)	
PE/VC/BDC						433.72***	438.04***	
						(11.80)	(11.10)	
Hedge fund/IM						455.08***	433.69***	
						(8.99)	(9.08)	
Insurance						91.59	85.37	
						(1.57)	(1.62)	
Ln(Amount)			2.67	-2.51	14.00	-7.09	0.84	0.26
			(0.28)	(-0.23)	(1.52)	(-1.05)	(0.13)	(0.01)
Performance pricing			-56.52***	-38.31***	-51.52***	-51.47***	-47.08***	-51.90
			(-4.71)	(-3.05)	(-4.28)	(-4.88)	(-4.60)	(-1.61)
Upfront fee				0.70***				
				(3.22)				
Annual fee				1.10***				
				(3.63)				
Warrants			83.33**	94.17**	58.04	41.76	7.84	5.98
			(2.25)	(2.34)	(1.35)	(1.26)	(0.21)	(0.05)
Convertible debt			-194.27***	-201.01***	-226.55***	-274.15***	-299.53***	-201.48
			(-3.46)	(-3.55)	(-3.69)	(-4.77)	(-4.72)	(-1.43)
Financial covenants			-7.28	-28.53	0.66	23.85	26.30	53.72
			(-0.32)	(-1.22)	(0.03)	(1.20)	(1.32)	(1.03)
Security			42.03*	28.45	23.21	61.95***	43.05**	-27.96
			(1.80)	(1.25)	(1.05)	(3.20)	(2.45)	(-0.48)
Second lien			405.06***	382.83***	360.30***	356.75***	333.17***	314.22***

			(6.84)	(4.49)	(5.82)	(6.63)	(5.66)	(3.20)
Maturity			-12.46**	-12.35**	-8.77**	-5.52	-2.62	-0.25
			(-2.53)	(-2.50)	(-2.20)	(-1.25)	(-0.70)	(-0.03)
Fixed rate loan			194.37***	179.97***	203.30***	154.80***	159.95***	190.37***
			(4.96)	(4.42)	(5.50)	(5.00)	(5.19)	(2.80)
Seniority			-109.80***	-113.67***	-141.69***	-65.24**	-80.19***	-70.85
			(-3.06)	(-2.74)	(-3.91)	(-2.07)	(-2.63)	(-0.81)
Ln(Assets)		-54.88***	-37.26***	-28.98*	-42.13***	-25.20***	-29.26***	-30.43
		(-7.02)	(-2.62)	(-1.95)	(-3.20)	(-2.93)	(-3.56)	(-0.57)
Profitability		-240.33***	-224.46***	-193.82***	-186.94***	-195.75***	-149.24**	-210.95
		(-3.44)	(-3.53)	(-3.04)	(-2.73)	(-3.47)	(-2.41)	(-1.42)
Leverage		178.06***	153.19***	151.32***	124.75***	146.08***	122.11***	116.18
		(4.33)	(4.56)	(4.46)	(3.48)	(4.85)	(4.01)	(1.15)
Research		-30.76	-93.88	-66.77	-37.37	-141.79**	-99.32	222.54
expense		(-0.34)	(-1.14)	(-0.80)	(-0.45)	(-2.01)	(-1.30)	(0.60)
PP&E		-85.89	-84.80*	-93.19**	-85.34**	-69.46*	-70.57**	119.24
		(-1.63)	(-1.92)	(-2.07)	(-2.17)	(-1.90)	(-2.16)	(0.50)
Cash		-107.84	-114.23	-109.57	-159.62**	-66.48	-112.81**	-177.21
		(-1.44)	(-1.56)	(-1.46)	(-2.46)	(-1.11)	(-2.09)	(-0.86)
Receivables		-260.39**	-258.75**	-264.14**	-280.10***	-196.68***	-209.16***	-388.16
		(-2.48)	(-2.34)	(-2.34)	(-2.62)	(-2.63)	(-2.93)	(-1.38)
Inventory		-38.87	-56.03	-101.36*	-35.31	-31.19	-10.74	251.33
		(-0.59)	(-1.00)	(-1.73)	(-0.69)	(-0.65)	(-0.25)	(0.70)
Ln(Firm age)		-7.84	-5.27	-8.43	-12.07	-7.04	-16.20**	47.47
		(-0.66)	(-0.44)	(-0.71)	(-1.07)	(-0.84)	(-2.16)	(0.30)
Market-to-book					-4.22		-6.17	-3.38
					(-0.67)		(-1.02)	(-0.16)
Sales growth					24.66		2.48	-59.62
					(0.91)		(0.10)	(-1.03)
Volatility					135.72***		105.47***	72.26
					(3.44)		(2.90)	(0.95)
Past return					-67.48***		-51.98***	-37.00
					(-3.55)		(-2.83)	(-1.15)
Constant	426.98***	777.34***	810.11***	794.99***	771.22***	658.65***	644.14***	163.32
	(14.80)	(10.42)	(8.28)	(7.97)	(8.36)	(9.48)	(9.13)	(0.21)
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	1145	1089	1052	902	981	1047	976	981

Table 7: Non-price terms of bank versus nonbank loans

This table reports the results from OLS regressions of non-price loan terms on lender type indicators, loan and firm characteristics. The sample includes all borrowings of a random sample of 750 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. Fixed rate loans by definition do not feature performance pricing and are dropped from the regressions for performance pricing. Even-numbered columns also include research expense, tangibility, cash, receivables, inventory, log firm age, market-to-book, sales growth, volatility and past returns as additional controls. The coefficients on these variables are not reported to save space. Variable definitions are in Appendix B. Industry fixed effects are based on Fama-French 12 industries. *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

Panel A: Basic non-price terms

	(1) Ln(Amount)	(2) Ln(Amount)	(3) Maturity	(4) Maturity	(5) Seniority	(6) Seniority	(7) Security	(8) Security
Bank FCO	-1.01***	-1.04***	0.50	0.57	-0.11*	-0.12**	0.10***	0.08*
	(-3.40)	(-2.67)	(0.99)	(1.37)	(-1.73)	(-2.06)	(2.75)	(1.96)
FCO	-0.88***	-0.26**	-0.40*	0.04	-0.13***	-0.13***	0.07**	0.02
	(-4.50)	(-2.03)	(-1.69)	(0.19)	(-2.80)	(-2.74)	(2.03)	(0.58)
Investment bank	0.88***	0.23	0.81***	0.47*	-0.13**	-0.15**	0.02	0.03
	(2.86)	(1.30)	(2.68)	(1.80)	(-2.04)	(-2.21)	(0.37)	(0.50)
PE/VC/BDC	-1.90***	-0.43***	-0.67***	0.44	-0.41***	-0.43***	-0.06	-0.15**
	(-8.76)	(-2.76)	(-2.69)	(1.55)	(-5.61)	(-5.70)	(-1.18)	(-2.55)
Hedge fund/IM	-1.77***	-0.44**	-1.01***	0.06	-0.37***	-0.38***	-0.21***	-0.28***
	(-6.97)	(-2.48)	(-3.55)	(0.27)	(-4.17)	(-4.88)	(-2.71)	(-4.22)
Insurance	0.12	-0.62**	5.85***	5.48***	-0.06	-0.06	-0.25**	-0.21*
	(0.38)	(-2.55)	(8.06)	(9.59)	(-1.10)	(-0.99)	(-2.11)	(-1.92)
Ln(Assets)		0.86***		0.29***		0.02**		-0.04***
		(20.14)		(4.37)		(2.03)		(-2.86)
Profitability		0.16		1.21***		-0.10		0.03
		(0.65)		(2.79)		(-1.26)		(0.31)
Leverage		0.61***		-0.09		-0.10*		0.07
		(3.41)		(-0.29)		(-1.68)		(1.07)
Constant	3.71***	-1.50***	3.62***	1.68***	0.97***	0.93***	0.84***	1.21***
	(27.51)	(-4.40)	(23.60)	(3.19)	(54.41)	(9.60)	(28.20)	(10.23)
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1083	1083	1069	1069	1084	1084	1058	1058

Panel B: Performance-related non-price terms

	(1) Financial covenants	(2) Financial covenants	(3) Performance pricing	(4) Performance pricing	(5) Warrants	(6) Warrants	(7) Convertible	(8) Convertible
Bank FCO	-0.22**	-0.23**	-0.08	-0.01	0.02	0.05*	-0.00	-0.01
	(-2.39)	(-2.36)	(-0.85)	(-0.06)	(0.77)	(1.72)	(-0.77)	(-1.13)
FCO	-0.20***	-0.12*	-0.38***	-0.26***	0.11**	0.07*	0.04*	0.03
	(-3.27)	(-1.91)	(-11.86)	(-6.06)	(2.50)	(1.96)	(1.70)	(1.29)
Investment bank	-0.11	-0.14**	-0.16*	-0.19**	0.04	0.05	0.12**	0.12**
	(-1.50)	(-2.12)	(-1.89)	(-2.25)	(1.07)	(1.26)	(2.04)	(2.04)
PE/VC/BDC	-0.46***	-0.35***	-0.43***	-0.31***	0.39***	0.27***	0.21***	0.19***
	(-6.84)	(-5.12)	(-15.26)	(-6.58)	(6.02)	(4.18)	(3.91)	(3.35)
Hedge fund/IM	-0.61***	-0.48***	-0.33***	-0.30***	0.25***	0.17***	0.28***	0.24***
	(-10.73)	(-8.07)	(-3.85)	(-2.90)	(4.04)	(2.68)	(6.09)	(5.26)
Insurance	-0.06	-0.10	-0.47***	-0.64***	0.03	0.04	-0.00	0.01
	(-0.87)	(-1.50)	(-9.67)	(-9.30)	(0.61)	(1.31)	(-0.71)	(0.79)
Ln(Assets)		0.03**		0.07***		-0.01		-0.00
		(2.19)		(4.50)		(-1.45)		(-0.41)
Profitability		0.20**		0.05		-0.26***		-0.04
		(2.17)		(0.44)		(-3.49)		(-0.56)
Leverage		0.07		-0.23***		-0.04		0.02
		(1.11)		(-2.66)		(-0.84)		(0.63)
Constant	0.85***	0.71***	0.35***	0.02	0.02*	0.14**	0.01	0.07
	(28.80)	(5.62)	(8.69)	(0.16)	(1.74)	(2.31)	(0.67)	(1.14)
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1085	1085	839	839	1084	1084	1084	1084

Panel C: Other loan terms

	(1) Fixed rate loan	(2) Fixed rate loan	(3) Upfront fee (bp)	(4) Upfront fee (bp)	(5) Annual fee (bp)	(6) Annual fee (bp)	(7) Second lien	(8) Second lien
Bank FCO	0.35**	0.34**	-1.63	-3.28	-1.76**	-0.25	0.02	0.01
	(2.05)	(2.24)	(-0.23)	(-0.56)	(-2.01)	(-0.19)	(0.70)	(0.62)
FCO	0.22***	0.19***	37.11***	23.86**	15.73	14.37	0.04*	0.05*
	(3.69)	(3.23)	(3.02)	(1.99)	(1.55)	(1.47)	(1.74)	(1.84)
Investment bank	0.17**	0.17**	47.40**	43.18**	-1.34	-0.15	0.08	0.08*
	(2.30)	(2.38)	(2.50)	(2.45)	(-1.50)	(-0.11)	(1.65)	(1.65)
PE/VC/BDC	0.66***	0.59***	15.55	-11.10	1.12	-1.23	0.04	0.06**
	(10.83)	(8.88)	(1.49)	(-0.91)	(0.37)	(-0.29)	(1.56)	(2.00)
Hedge fund/IM	0.79***	0.73***	33.15***	8.36	1.76	0.02	0.02	0.03
	(18.30)	(14.73)	(2.84)	(0.60)	(0.73)	(0.01)	(1.17)	(1.35)
Insurance	0.86***	0.89***	0.30	5.53	-2.72***	-1.65	-0.01*	-0.02*
	(17.99)	(18.73)	(0.02)	(0.48)	(-3.13)	(-1.06)	(-1.96)	(-1.94)
Ln(Assets)		-0.02		-5.02***		-0.74		-0.00
		(-1.21)		(-2.74)		(-1.33)		(-0.80)
Profitability		-0.08		-24.89		1.08		0.04*
		(-1.01)		(-1.58)		(0.29)		(1.71)
Leverage		0.02		13.61		-4.31*		0.01
		(0.40)		(1.34)		(-1.90)		(0.34)
Constant	0.06***	0.16	22.21***	45.46**	5.22**	8.80	0.00	0.01
	(2.97)	(1.44)	(4.35)	(2.44)	(2.22)	(1.46)	(0.47)	(0.37)
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1057	1057	919	919	923	923	1085	1085

Table 8: 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: log of total assets, leverage, market-to-book, sales growth, R&D, PP&E, cash, receivables, inventory, log of firm age, volatility, past stock returns, the year of loan origination, and industry effects. The estimation for performance pricing omits fixed rate loans. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Bandwidth	Left obs.	Right obs.	1st stage	2nd stage
Initial interest rate	32.48	194	346	-0.30***	564.79***
				(-4.03)	(4.10)
Ln(Amount)	22.06	193	318	-0.29***	-0.43
				(-3.53)	(-0.69)
Maturity	22.88	187	317	-0.31***	-2.39*
				(-3.72)	(-1.73)
Seniority	28.16	201	350	-0.30***	-0.06
				(-3.93)	(-0.15)
Security	29.96	204	354	-0.30***	-0.15
				(-4.07)	(-0.62)
Second lien	27.54	202	346	-0.29***	-0.03
				(-3.73)	(-0.88)
Financial covenants	23.52	195	326	-0.29***	-0.58**
				(-3.59)	(-2.22)
Performance pricing	24.50	105	256	-0.23***	-0.10
				(-2.67)	(-0.20)
Warrants	22.76	192	321	-0.30***	0.42*
				(-3.60)	(1.86)
Convertible	22.48	192	320	-0.29***	0.10
				(-3.62)	(0.49)
Fixed rate loan	24.14	192	318	-0.29***	0.35
				(-3.54)	(1.20)
Upfront fee	18.61	169	235	-0.25***	71.74
				(-2.72)	(1.44)
Annual fee	33.14	187	312	-0.28***	31.05*
				(-3.61)	(1.73)
$Bankrupt_{t+3}$	20.25	168	275	-0.25***	0.04
				(-2.79)	(0.14)
Δ $Profitability_{t+1}$	36.87	202	395	-0.27***	0.17
				(-3.75)	(1.13)
Δ $Profitability_{t+2}$	25.32	178	291	-0.28***	-0.07
				(-3.19)	(-0.67)
Δ $Profitability_{t+3}$	19.29	139	218	-0.22**	0.38
				(-2.13)	(1.20)

Table 9: Matching estimates for loan characteristics

This table provides results of a nearest-neighbor matching using Mahalanobis distance between borrowers from nonbanks (*treated*) and banks (*control*). To create the control group, we utilize Mahalanobis matching with exact matching for loan origination year in addition to (nearest neighbor) matching on borrowing firm Profitability and Leverage. Panel A provides the covariate balance of the sample before and after the matching used to estimate the ATET for interest rates (as presented in the first column of Panel B). Panel B reports average treatment effect on the treated (ATET) with Abadie-Imbens (AI) robust standard errors in the parentheses for loan amount, initial interest rate, and maturity in columns 1-3, respectively. The sample includes all borrowings of a random sample of 750 middle-market firms originated during the 2010-2015 period. Observations are aggregated to the deal level using the average value of each variable across the tranches in a deal. Initial interest rate is equal to the fixed rate for fixed rate loans and to 3-month LIBOR plus spread for floating rate loans. Variable definitions are in Appendix B. ATET is bias-adjusted by using firm size (Ln (Assets)), Profitability, Leverage, Research expense, PP&E, Cash, Receivables, Inventory, Ln (Firm Age), Volatility, Past stock returns. 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)	-0.471	-0.234	1.397	1.146
Profitability	-0.701	-0.145	3.587	1.516
Leverage	0.426	0.099	1.710	1.238
Research expense	0.262	0.000	3.099	1.149
PP&E	-0.141	-0.001	0.862	0.907
Cash	0.040	-0.090	1.481	0.863
Receivables	0.142	0.177	1.410	1.171
Inventory	-0.028	-0.150	0.962	0.604
Ln (Firm Age)	-0.343	-0.221	1.108	1.083
Volatility	0.640	0.289	1.969	1.338
Past Returns	-0.383	-0.240	1.802	1.401

Panel B: Matching Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Interest Rate	Ln (Amount)	Seniority	Security	Financial Covenants	Warrants
ATET						
Nonbank Dummy	334.21***	-0.399***	-0.203***	-0.122***	-0.287***	0.153***
(AI robust *std. errors)*	(21.38)	(0.114)	(0.029)	(0.031)	(0.040)	(0.024)
N (Matched Observations)	664	688	690	688	690	690
Bias-adj. Variables	Ln (Assets), Profitability, Leverage, Research expense, PP&E, Cash, Receivables, Inventory, Ln (Firm Age), Volatility, and Past Returns					

Table 10: Probability of bankruptcy for bank versus nonbank loans

This table reports the results from linear probability models of borrower's bankruptcy over the three years after loan origination. The sample includes all borrowings of a random sample of 750 middle-market firms originated from January 2010 through May 2015. Bankruptcy dates as of May 31, 2018 are from Capital IQ. There are 53 deals by 32 borrowers that result in bankruptcy within three years. Variable definitions are in Appendix B. Industry fixed effects are based on Fama-French 12 industries. *z*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)
Nonbank	0.041**	0.032*	0.026	0.012
	(2.37)	(1.88)	(1.50)	(0.70)
Ln(Assets)		0.004	-0.000	0.010
		(0.80)	(-0.02)	(1.16)
Profitability		-0.102***	-0.112**	-0.061
		(-2.61)	(-2.26)	(-1.14)
Leverage			0.054	0.044
			(1.46)	(1.13)
PP&E			-0.016	-0.008
			(-0.32)	(-0.16)
Cash			-0.017	0.020
			(-0.26)	(0.30)
Receivables			-0.101	-0.068
			(-1.30)	(-0.89)
Inventory			-0.073	-0.043
			(-1.25)	(-0.74)
Research expense			-0.055	-0.032
			(-0.81)	(-0.50)
Ln(Firm age)			0.004	-0.000
			(0.39)	(-0.04)
Market-to-book				-0.002
				(-0.28)
Sales growth				-0.008
				(-0.26)
Volatility				0.094**
				(2.54)
Past return				-0.084***
				(-3.46)
Constant	0.009	-0.022	0.016	-0.088
	(0.47)	(-0.76)	(0.27)	(-1.08)
Year effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Observations	1165	1118	1109	1029

Table 11: Future performance by lender type

This table reports the results of regressions of year-to-year changes in borrower's profitability on the nonbank lender dummy and borrower characteristics. The sample includes all borrowings of a random sample of 750 middle-market firms originated during the 2010-2015 period. Variable definitions are in Appendix B. Industry fixed effects are based on Fama-French 12 industries. *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)	(6)
	[*t*,*t*+1]	[*t*+*1*,*t*+2]	[*t*+*2*,*t*+3]	[*t*,*t*+1]	[*t*+*1*,*t*+2]	[*t*+*2*,*t*+3]
Nonbank	-0.02*	-0.01	0.00	-0.01	-0.01	-0.00
	(-1.96)	(-1.44)	(0.06)	(-0.71)	(-1.27)	(-0.22)
Ln(Assets)	0.01	0.01	-0.00	0.00	0.00	-0.00
	(1.63)	(1.50)	(-0.94)	(0.83)	(0.73)	(-1.01)
Profitability	-0.51***	-0.10**	-0.03	-0.50***	-0.10	-0.05
	(-10.15)	(-2.03)	(-0.52)	(-8.60)	(-1.61)	(-0.86)
Leverage	0.05*	0.05**	-0.01	0.07**	0.04	-0.01
	(1.87)	(2.05)	(-0.31)	(2.57)	(1.49)	(-0.36)
Research expense	-0.06	-0.06	-0.13*	-0.13	-0.13	-0.06
	(-0.63)	(-0.73)	(-1.83)	(-1.26)	(-1.36)	(-0.67)
PP&E	0.01	0.02	-0.01	0.02	0.02	0.01
	(0.60)	(1.00)	(-0.38)	(1.00)	(0.85)	(0.44)
Cash	-0.14***	-0.02	-0.02	-0.14***	-0.05	-0.00
	(-2.65)	(-0.54)	(-0.30)	(-2.77)	(-1.01)	(-0.00)
Receivables	-0.03	0.08*	-0.04	0.02	0.09*	-0.01
	(-0.53)	(1.94)	(-0.73)	(0.42)	(1.83)	(-0.14)
Inventory	-0.07**	0.05*	-0.01	-0.05	0.06**	-0.01
	(-2.07)	(1.94)	(-0.26)	(-1.58)	(2.02)	(-0.29)
Ln(Firm age)	-0.00	0.00	-0.00	0.00	-0.00	0.00
	(-0.09)	(0.01)	(-0.33)	(0.67)	(-0.36)	(0.32)
Market-to-book				0.00	0.01	-0.01**
				(0.68)	(1.30)	(-2.14)
Sales growth				0.03**	-0.02	0.06***
				(2.05)	(-0.72)	(2.70)
Volatility				-0.07***	-0.02	-0.00
				(-3.08)	(-0.69)	(-0.04)
Past return				0.02	-0.03**	0.03
				(0.97)	(-2.37)	(1.43)
Constant	0.04	-0.07*	0.06	0.07*	-0.03	0.04
	(1.03)	(-1.90)	(1.36)	(1.73)	(-0.62)	(0.86)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1129	1045	880	1051	972	813

Table 12: Announcement returns around loan origination

This table reports the results of regressions of cumulative announcement returns around loan origination. The sample is limited to loans whose origination is disclosed through an 8-K filed within five calendar days of loan origination and for which the last stock price before loan origination is at least $1. Columns 1-3 report market-model adjusted cumulative returns from loan origination through announcement date. Columns 4-6 report market-model adjusted cumulative returns on the announcement date. Announcement date is determined based on the time the 8-K was uploaded to EDGAR; if submission time is after the market close, announcement date is set to the next trading date. Market beta is estimated over the [-385, -20] period relative to loan origination, requiring at least 120 daily observations. Heteroscedasticity robust *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	[Origination, Announcement]			[Announcement, Announcement]		
	(1)	(2)	(3)	(4)	(5)	(6)
Nonbank	0.033***	0.034***	0.029**	0.015**	0.010	0.013
	(3.38)	(3.28)	(2.30)	(2.04)	(1.25)	(1.22)
Ln(Assets)		0.001	0.001		0.001	0.002
		(0.23)	(0.37)		(0.56)	(0.96)
EBITDA < 0		-0.015	-0.023		0.013	0.011
		(0.76)	(1.14)		(1.18)	(0.88)
Leverage		0.026	0.026		0.012	0.011
		(1.42)	(1.42)		(1.14)	(1.03)
Financial covenants			-0.012			0.008
			(0.89)			(0.90)
Warrants			0.014			0.010
			(0.63)			(0.81)
Maturity			-0.001			-0.001
			(0.54)			(0.75)
Constant	0.002	-0.008	0.008	0.003	-0.008	-0.015
	(0.68)	(0.36)	(0.32)	(1.19)	(0.57)	(0.77)
Observations	324	317	312	324	317	312