How Collateral Affects Small Business Lending: The Role of Lender Specialization

Manasa Gopal*

November 1, 2019

Job Market Paper
CLICK HERE FOR LATEST VERSION

Abstract

I study the role of collateral on the distribution of credit to small business borrowers in a crisis. I construct a novel dataset on loan-level, secured small business lending in the U.S. and link it to the U.S. Census of Establishments. Using textual analysis, I quantify the level of matching between borrowers and lenders by comparing the borrower's collateral to the collateral specialization of the lender. I show that, after the start of the 2008 financial crisis, lenders rationed credit by increasing their specialization in collateral. Borrowing firms that were weakly matched to their lenders on collateral received fewer loans. I show that this effect holds within-firms, and within-lenders. I identify the channel affecting lender behavior and show that it is driven by the lender's informational advantage in the collateral that is posted. I further show that firms with collateral that is more generally accepted find it easier to obtain credit from new lenders, directly affecting small business employment outcomes. In sum, this paper documents a new channel for the allocation of credit to small business borrowers over a business cycle.

*New York University Stern School of Business, mgopal@stern.nyu.edu. I am grateful to Philipp Schnabl (Chair), Anthony Saunders, and Viral Acharya for extensive guidance and support. I would like to thank Nicola Cetorelli, Adam Copeland, Abhinav Gupta, Arpit Gupta, Sabrina Howell, Kose John, Theresa Kuchler, Simone Lenzu, Andres Liberman, David Lucca, Stephan Luck, Holger Mueller, Cecilia Parlatore, Fahad Saleh, Asani Sarkar, Alexi Savov, Johannes Stroebel, James Vickery, Siddharth Vij, Iris Yao, and seminar participants at the Federal Reserve Bank of New York and NYU Stern for helpful comments. Part of this paper was completed during the Dissertation Internship at the Federal Reserve Bank of New York in the summer of 2019. The research in this paper was conducted while the author was a Special Sworn Status researcher of the U.S. Census Bureau at the Center for Economic Studies. Research results and conclusions expressed are those of the author and do not necessarily reflect the views of the Census Bureau. This paper has been screened to ensure that no confidential data are revealed.

1 Introduction

How does collateral affect the distribution of credit to borrowers in a downturn? The answer to this question is crucial for understanding the heterogeneous effects of credit supply shocks. Collateral plays a central role in small business credit access, with over 88.5% of small business loans backed by collateral in 2016.[1] If lenders are differentially equipped to evaluate the collateral of a borrower, i.e. lenders are specialized, then credit supply to the borrower may differ based on the specialization of the lender. In this paper, I investigate the link between lender collateral specialization, borrower-lender matching on collateral, and firm outcomes in the aftermath of the 2008 financial crisis in the U.S.

To understand why collateral may affect lender behavior, consider the trade-offs faced by the lender. On the one hand, collateral serves to reduce a lender's risk and default loss when providing credit. Collateral reduces lender loss by helping screen observationally identical borrowers, reducing moral hazard, and by allowing the lender to foreclose on the borrower's collateral in case of default.[2] On the other hand, the use of collateral is costly for lenders. They incur the cost of monitoring, screening, as well as disposing off collateral.[3] Differences in the benefits and costs of collateral may vary by collateral type and lender, driven by informational advantages or lender expertise. These advantages become consequential in a downturn. As borrower default probabilities increase, the relative importance of collateral for credit access increases. If lenders have a comparative advantage in evaluating certain categories of collateral and not others, it can affect the set of firms receiving credit. This, in turn, can have first order effects on real outcomes.

There are two main challenges in understanding how lender specialization affects the allocation of credit. The first challenge is the lack of data on firm-level borrowing and firm collateral for small businesses in the U.S. Studies on the financial crisis have largely focused

[1] Loans below $1 million. Survey of Terms of Business Lending, Federal Reserve Board. Source - https://www.federalreserve.gov/releases/e2/201612/default.htm

[2] Collateral can serve as a signaling device reducing adverse selection (Stiglitz and Weiss (1981), Besanko and Thakor (1987a), Besanko and Thakor (1987b), Bester (1985), Bester (1987), and Chan and Thakor (1987)), moral hazard (Boot, Thakor, and Udell (1991), Boot and Thakor (1994), and Holmstrom and Tirole (1997)), and by increasing contract enforceability (Albuquerque and Hopenhayn (2004) and Cooley, Marimon, and Quadrini (2004))

[3] See Leeth and Scott (1989)

on European markets or on large, syndicated loans in the U.S. due to the lack of detailed lending data for small businesses in the U.S. However, small businesses are most likely to be affected by credit supply shocks. Nearly all small businesses in the U.S. are privately held and lack access to public capital markets. With fewer options to substitute credit, small businesses rely on debt for financing investment and growth. Thus, studies on large U.S. businesses or in regions with different banking and financial environments may underestimate the true effect of a financial crisis on the U.S. economy.[4]

I address this challenge by collecting a novel dataset covering all collateralized loans in Texas between 2002 and 2016. The matched borrower-lender loan data is collected from public records filed under the Uniform Commercial Code (UCC). I further link the loan-level data to the U.S. Census of establishments for borrower outcomes. My paper is one of the first to create a quasi credit registry for the U.S. using detailed information on borrower and lender collateral. As an added advantage, my dataset contains information on non-bank lenders such as finance companies who constitute nearly half of total small business lending in the U.S., but are often ignored in the academic literature. My final dataset contains 486,000 loans to 93,000 firms from over 600 lenders between 2002 and 2016.

The second challenge in addressing my research question is the non-random matching between borrowers and lenders. Firms that match to lenders specialized in their collateral may be intrinsically different from firms with matches to unspecialized lenders. Or conversely, lenders that are more specialized (lending only to borrowers whose collateral they have expertise in) may respond differentially when credit supply is constrained compared to more diversified lenders. For identification, therefore, I exploit variation in credit supply to the *same* firm for multi-relationship borrowers, as well as the variation across borrowers of the *same* lender.

To identify the impact of lender specialization on credit allocation, I use textual analysis to create a measure of *Firm-Lender Collateral Match Quality*. The goal of this measure is to capture the extent of specialization of a lender in the collateral of the borrower. The

[4]Small businesses are independently important, contributing nearly 50% of employment in the economy, and generating 2 out of the 3 net new private sector jobs. Source: Small Business Administration https://www.sba.gov/sites/default/files/advocacy/Frequently-Asked-Questions-Small-Business-2018.pdf

assumption underlying this measure is that lenders have greater expertise in the collateral that occurs more frequently in their loan portfolios, after accounting for the aggregate availability of the collateral in the economy.[5] Using loans originated between 2002 and 2007 (the pre-crisis period), each firm-lender pair is assigned a numerical value based on the textual similarity of the firm's collateral to the lending portfolio of its relationship lenders. This is a measure bounded between 0 and 1 with higher values indicating greater match quality. The goal of this paper is to identify whether differential match quality on collateral affects borrower access to credit in the aftermath of the financial crisis.

To further clarify the methodology, consider the following example. Firm A borrows from two lenders - Frost National Bank and Financial Federal Credit Inc. The borrower pledges trucks to both these lenders. Approximately 4.5% of Frost National Bank's collateral portfolio consists of trucks while 34% of Financial Federal Credit's loans are made against trucks as collateral. The Firm-Lender Collateral Match Quality between Firm A and Financial Federal Credit will be higher than the match quality between Firm A and Frost National Bank. The focus of this paper is thus to explore whether Firm A is more likely to receive credit from Financial Federal Credit in the downturn than from Frost National Bank due to a superior borrower-lender collateral match.

To identify the causal effect of lender collateral specialization in collateral on credit supply, I focus on the sample of firm-lender pairs with a relationship in the pre-crisis (2002-07) period. Using a *within*-firm and *within*-lender estimator, I show that a one standard deviation increase in Firm-Lender Collateral Match increases the probability of receiving a new loan, after the start of the crisis, by 17.85% above the unconditional mean.

Next, I evaluate the potential sources of lender advantage driving the specialization of lenders in the aftermath of the financial crisis. My main focus is on the distinction between lending advantages that are *collateral-specific* from those that are industry-specific or firm-specific. While collateral specialization can be considered one aspect of industry specialization, I show that the effect of collateral match persists even after the inclusion of controls for lender specialization in an industry, and by looking across borrowers within the

[5]Based on the theoretical literature (Winton (1999), Dell'Ariccia, Friedman, and Marquez (1999)) that suggests that lender's concentration in a sector implies expertise

same lender-industry cell. I find that after controlling for lender specialization in the 6-digit NAICS industry of the borrower, a one standard deviation in Firm-Lender Collateral Match increases the probability of receiving a new loan by 3.54%, which is equivalent to 17% of the mean probability of receiving a loan.

Second, I test whether lending advantages are driven by specialization in collateral or firm-specific knowledge, such as soft information. As discussed extensively in the banking literature, lenders accumulate private information about the firm during the course of business, which affect their lending decisions. Thus, I include proxies for borrower-lender relationship strength as controls in the baseline specification. These include the number of loans to the firm from the lender in the pre-crisis period, the share of the lender in total lending to the firm pre-crisis, and time from last loan to the borrower from the lender. While these measures may themselves be correlated to the collateral match between the borrower and the lender (i.e., more loans from the lender because of expertise in collateral), I show that a one standard deviation increase in collateral match including industry controls leads to a 10.1% higher likelihood of getting a new loan compared to 17.9% higher likelihood without the controls. As an alternate test for soft information, I study how firm-lender collateral match of *new* borrowers of the lender compare to its current set of borrowers. For new borrowers, the lender does not have private, firm-specific information. If the new set of borrowers, however, are closely related to the lender's collateral specialization, it provides further support to my contention that collateral specialization drives lender behavior, rejecting the null that collateral does not differentially affect credit supply across lenders. I show that this is the case.

Next, I evaluate the reasons driving lender specialization in collateral. I argue that lender specialization is driven by informational advantages of the lender (which may include ex-ante private asymmetric information about the quality of collateral, or greater ability to redeploy the collateral ex-post through the presence of existing infrastructure for collateral storage and disposal, network of potential buyers etc.) by eliminating other potential channels for lender specialization. First, I show that lending behavior is not driven by the type of business the lender is involved in. Traditionally, banks are thought to do more cash-based lending (evaluate firms based on projected cash flows) while finance companies tend to lend against collateral values. For some lenders in the sample, specifically captive finance companies, increasing collateral sales and collateral value may be the primary motivation for lending. I find that these differences do not explain the observed specialization patterns.

Second, lenders may concentrate new lending to otherwise distressed borrowers to reduce the probability of having to recognize loan losses on old loans and thus, reduce charges against their loss reserves and capital. If the firm-lender collateral match captures the level of prior lending or commitments of the lender, they may be inclined to continue lending to borrowers with higher collateral match to prevent losses on their loan portfolio. I show, however, that low-capitalization banks, who are most likely to have such motives to distort lending, do not behave differently from high-capitalization banks.

Third, an alternate hypothesis for change in lender behavior could be concerns about fire-sale discounts.[6] Lenders may concentrate their lending portfolio, in a crisis, on the types of collateral least likely to face losses in the event of borrower default. In this case, lenders would concentrate lending on the most redeployable assets in the economy which, in turn, are likely to be the most liquid and least prone to fire-sale discounts. If, on average, lenders are more specialized in assets that are more redeployable, a shift to redeployable collateral would line up with a shift to collateral the lender is more specialized in. To test whether fire-sale concerns drive lender behavior, I test how lenders respond to industry distress. In the case that lender behavior is driven by fire-sales concerns and not collateral specialization, lenders would be less likely to lend to distressed industries that face greater fire-sale discounts even if they have greater specialization in the collateral. However, importantly, I show that the effect of Firm-Lender Collateral Match Quality on lending does not vary by level of industry distress.

After documenting the important role of collateral specialization of lenders for credit access within a firm, I extend my analysis to study the effect of collateral match quality on firm-level outcomes. By focusing on firm-outcomes, I account for ability of the borrower to substitute to new lenders. For the firm-level results, I create a measure of *Firm Collateral Match* as the weighted average of firm-lender collateral match qualities. I show that greater the aggregate measure of firm match quality, larger the availability of credit to firms from

[6]See Shleifer and Vishny (1992)

its relationship lenders. A one standard deviation increases in Firm Collateral Match leads to 3.19% increasing in lending from relationship lenders, equivalent to 10.35% of the mean probability of a repeat loan. I then test how firm matching to relationship lenders affects total credit available to the firm. I show that firms partially substitute credit from new lenders. In fact, after the start of the financial crisis, nearly half the firms in the sample borrow from a lender with no prior relationship. This offsets some of the difference in lending driven by low lender collateral match.

To study the ability of firms to substitute, I once again focus on borrower collateral. I create a measure of *Firm Collateral Similarity* by comparing the collateral of the firm to the (weighted) average lender in the economy. This measure quantifies the ease of firm borrowing in the economy given its collateral. I show that firms with greater overall similarity (i.e. more lenders lending against the firm's collateral) are more likely to substitute to new lenders in a crisis. A one standard deviation increase in Firm Similarity increases the probability of borrowing from a new lender by 3.4%. Total lending to the firm, furthermore, is a function of the overall ability of the firm to borrow given its collateral. A one standard deviation increase in Firm Similarity increases total lending by 6.0%. Finally, I show that firm's match quality and overall asset commonality can have real implications affecting firm employment during the crisis, and the pace of recovery following the financial crisis. A one standard deviation increase in firm collateral similarity increases the average level of post-crisis firm employment by 3.36%

Finally, a few caveats are in order. While I observe the extensive margin of credit allocation, my data prevents the observation of either loan quantity or loan pricing. Thus, I consider the extensive margin results to be a lower bound on the true impact of a crisis on small business credit. However, as to pricing, Petersen and Rajan (1994) show that, based on a survey of small businesses, availability of credit is altered on quantities, rather than prices. More recently, DeYoung, Gron, Torna, and Winton (2015) show that decrease in credit to SMEs during the crisis was caused not by increased pricing of credit risk but rather by quantity rationing. These papers provide credence to my measure of credit rationing.

In summary, this paper provides evidence on the important role of lender specialization in borrower collateral for firm outcomes in a downturn. I show that within-firm, and within-lender, a greater level of ex-ante collateral match between borrowers and lenders leads to increased credit supply in the aftermath of the financial crisis. This increase is due to lender specialization in collateral driven by informational advantage of the lender. I further show that quality of collateral match between the borrower and lender can have aggregate impact on total credit to the firm, as well as firm employment.

This paper relates to several strands of the literature. First, my paper relates to the role of lender specialization in credit allocation. Traditional banking theory argues for diversification across projects (Diamond (1984), Boyd and Prescott (1986)). Here, diversification reduces risks associated with idiosyncratic shocks lowering monitoring costs for lenders. This suggests banks should avoiding concentrating their lending portfolio. However, the argument relies on banks having equal expertise in all sectors of the economy.[7] But, lender specialization has been shown to be valuable as it helps in information collection (Loutskina and Strahan (2011), Berger, Minnis, and Sutherland (2017)), increase market valuations (Laeven and Levine (2007)), allows lenders to extract rents (Petersen and Rajan (1994), Rajan (1992)), and protects against market competition (Boot and Thakor (2000), Dell'Ariccia and Marquez (2004), Hauswald and Marquez (2006), Degryse and Ongena (2004)).[8]

Consequently, in practice, lenders tend to be specialized by type of borrower (Carey, Post, and Sharpe (1998)), or export markets (Paravisini, Rappoport, and Schnabl (2018)) among other areas. Liberti, Sturgess, and Sutherland (2017) document the role of lender specialization in collateral. While Liberti, Sturgess, and Sutherland (2017) show that collateral can affect lending decisions of lenders in new markets, I show that the extent to which borrower's collateral matters for credit supply changes with lender constraints. Thus, I add to the literature on lender specialization by documenting the important role of collateral in lender specialization decisions when lenders are constrained, and the important real economic consequences of lender specialization on borrowers.

Second, my paper relates to the literature on matching between borrowers and lenders

[7]Diversification may hurt as monitoring becomes weaker in new sectors (Winton (1999), Acharya, Hasan, and Saunders (2006), Berger, Hasan, and Zhou (2010)) or if resource allocation across divisions is inefficient (Rajan, Servaes, and Zingales (2000)). Furthermore, Fricke and Roukny (2018) show that high leverage can undo the benefits of diversification

[8]Private information of some lenders may also have externalities on other market players. See for example, Stroebel (2016) or Murfin and Pratt (2019)

in the economy. Prior work has shown that borrower-lender matching is influenced by geographic proximity (Petersen and Rajan (1995), Petersen and Rajan (2002)), bank size (Stein (2002), Hubbard, Kuttner, and Palia (2002), Cole, Goldberg, and White (2004)), or bank capital structure (Schwert (2018)). I extend this literature by documenting matching based on collateral, and studying the consequences of matching for credit and real outcomes. In Schwert (2018), under the assumption that observed matches are optimal, the paper explores borrower-lender characteristics that explain the match. Unlike his approach, I estimate the quality of matches between borrowers and lenders and document the consequences of changes in match quality. I also examine how borrower-lender matching changes over the business cycle. In this respect, the mechanism is similar to the one described by Granja, Leuz, and Rajan (2018) for geographic proximity.

Third, my paper relates to the role of collateral in lending. On the theoretical side, collateral arises naturally in settings with asymmetric information.[9] The importance of collateral has also been documented in the empirical literature.[10] I add to the literature on the importance of collateral by showing that the benefits to collateral vary by the type of collateral as well as by lender. I also focus on the dynamic role of collateral in lending decisions.

Fourth, my paper relates to the literature on the role asset specificity in lending. Starting with seminal work by Shleifer and Vishny (1992), the literature has documented the important role of asset fire sales and asset redeployability for credit access. The empirical literature has shown that firms with liquid collateral receive loans with longer maturity (Benmelech (2008)), lower spreads on loans, higher credit ratings, and higher LTV ratios (Benmelech and Bergman (2009), Almeida and Campello (2007)), and have a lower cost of

[9]Collateral can serve as a signaling device reducing adverse selection (Stiglitz and Weiss (1981), Besanko and Thakor (1987a), Besanko and Thakor (1987b), Bester (1985), Bester (1987), and Chan and Thakor (1987)), moral hazard (Boot, Thakor, and Udell (1991), Boot and Thakor (1994), and Holmstrom and Tirole (1997)), and by increasing contract enforceability (Albuquerque and Hopenhayn (2004) and Cooley, Marimon, and Quadrini (2004)). Collateral also arises in settings with costly state verification (as in Townsend (1979), Gale and Hellwig (1985), and Williamson (1986)), and to incentivize lender monitoring (Rajan and Winton (1995)).

[10]For reference, see Berger, Espinosa-Vega, Frame, and Miller (2011), Jiménez and Saurina (2004), Berger and Udell (1995), John, Lynch, and Puri (2003), Berger and Udell (1990), Brick and Palia (2007), Chakraborty and Hu (2006), Jiménez, Salas, and Saurina (2006), Berger, Frame, and Ioannidou (2011), Berger, Frame, and Ioannidou (2016)

capital (Ortiz-Molina and Phillips (2014)). Asset redeployability has been shown to be an important determinant of leverage for small businesses (Campello and Giambona (2013), Giambona, Mello, and Riddiough (2018)) with special importance during periods of distress (Pulvino (1998), Schlingemann, Stulz, and Walkling (2002), Acharya, Bharath, and Srinivasan (2007)).[11] Consistent with this literature, I show using detailed firm-level data, and comparison across industries, that firms with more commonly accepted collateral have a easier time substituting credit when faced with a supply shock. However, I add to this literature by documenting not only the importance of the type of collateral but the importance of the lender lending against the collateral.

Finally, my paper relates to the literature on credit supply during and in the aftermath of the financial crisis. The literature argues that changes in credit supply played an important role in triggering and amplifying the financial crisis.[12] Ivashina and Scharfstein (2010) document the drop in bank lending to large businesses following the bankruptcy of Lehman Brothers. Chen, Hanson, and Stein (2017), Bord, Ivashina, and Taliaferro (2018) document specifically the impact of the financial crisis on small business lending.[13] I add to this literature by documenting the heterogeneity in treatment across borrowers of the same lender. With detailed information on borrowers and lenders of small business loans, I document a new channel for the propagation of credit supply shocks to the economy.[14] Furthermore, I contribute to the literature documenting the real effects of credit supply shocks with detailed information linking small business lending to employment outcomes.[15]

The rest of the paper is organized as follows. Section 2 described the data sources and

[11] Shleifer and Vishny (2010) provide a full review of the fire sales literature. In contrast, Diamond, Hu, and Rajan (2019) argue that high asset pledgeability could hurt firms in a downturn. Collateral usefulness also depends on creditor rights (Calomiris, Larrain, Liberti, and Sturgess (2017), Vig (2013), Campello and Larrain (2015)), and ability to repossess the asset (Eisfeldt and Rampini (2008), Benmelech and Bergman (2008)). Furthermore, type of collateral pledged varies by firm characteristics (Liberti and Sturgess (2014), Mello and Ruckes (2017))

[12] Mian and Sufi (2009), Mian and Sufi (2018) argue that expansion in supply of mortgages was responsible for the boom and bust in housing markets, and the subsequent recession.

[13] Cortés, Demyanyk, Li, Loutskina, and Strahan (2018), Acharya, Berger, and Roman (2018), Covas (2018) argue that post-crisis stress testing of large banks led to decrease in small business lending.

[14] Chaney, Sraer, and Thesmar (2012), and Adelino, Schoar, and Severino (2015) document the importance of collateral channel using real estate as collateral

[15] See Bernanke (1983), Peek and Rosengren (2000), Benmelech, Meisenzahl, and Ramcharan (2016), Ashcraft (2005), Chodorow-Reich (2013), Greenstone, Mas, and Nguyen (2014), Bentolila, Jansen, and Jiménez (2017)

panel construction. Section 3 describes the text analysis techniques used in creating the measure of Firm-Lender Collateral Match Quality. Section 4 describes the identification strategy and empirical results. Section 5 concludes.

2 Data and Summary Statistics

2.1 Data Sources

The insights in this paper come from combining two data sources- UCC filings for information on firm-lender relationships and the Census of Establishments for firm outcomes.

2.1.1 UCC-1 Filings

My main dataset is sourced from state-level public records filed under the Uniform Commercial Code (UCC). The UCC is the set of laws that guide all commercial transactions in the U.S., such as sales, leases, and rentals. Article 9 of the UCC states that secured creditors have the right to make a public filing detailing their claim on borrower assets when originating a secured loan. In case of borrower default, these filings determine priority in bankruptcy proceedings. Secured lenders without an active UCC filing are considered unsecured creditors by law. For this reason, and due to the low cost of making UCC filings (typically \$15-\$25 for electronic filings), I believe my sample is representative of the universe of secured lending.

UCC filings under Article 9 are made for security interest in "personal-property". Filings are made at the state-level at respective Secretary of State offices in the state of the borrower.[16] Real estate transactions, while governed by the UCC laws, require lenders to make filings at local county offices responsible for tracking that piece of land.[17] Furthermore, properties with titles, such as automobiles, boats, and airplanes, generally do not require state-level UCC filings for liens.[18] Any other collateral pledged by borrowers must

[16]State of incorporation for registered businesses or headquarters for unincorporated businesses.

[17]63% of loans to small and medium-size businesses are backed by non real-estate collateral - see Calomiris, Larrain, Liberti, and Sturgess (2017)

[18]Recent court rulings have opened up debate on the need for UCC-1 filings on titled property. See for example - https://www.cscglobal.com/blog/court-finds-certificate-of-title-alone-not-

be detailed through a state-level UCC filing.

One of the biggest strengths of the UCC data is that it allows for the creation of a quasi credit registry for the U.S. including data on loans originated by non-bank players such as finance companies.[19] To the best of my knowledge, Edgerton (2012) is the only other paper that creates a similar registry from UCC filings for the U.S. by focusing on businesses in California over a six-year period. Murfin and Pratt (2019) use data on equipment financing sourced from UCC filings to study optimal pricing by captive finance companies. However, their paper only includes heavy equipment financing of firms in construction and agriculture. The biggest drawback of the UCC data is that we can only observe extension of credit. Loan terms such as loan amount or pricing information are unobservable.

2.1.2 Texas Data

For the majority of this paper, I focus on firms operating in Texas. To understand the role of firm-specific collateral on firm outcomes, I need detailed information on collateral pledged by firms. While this information is available at individual state offices, bulk download of historical data is either unavailable or prohibitively expensive. California and Texas are two states that allow for the bulk download of UCC filings. However, the California data only goes back for six years from the date of download (please see Edgerton (2012) for details).

The Texas Secretary of State website allows for the download of historical data starting from 1966. However, I restrict my sample to filings made from 2002 onwards. The main reason for this choice is a July 2001 change to the laws governing where UCC filings are to be made. Before this date, a UCC filing was required in every state in which a firm maintained assets. After 2001, the filing location was changed to the state of incorporation for incorporated businesses or the location of the CEO's office for unincorporated firms with multiple offices. Including data before 2002 might lead to repeat counting of the same loan to a business with multiple offices.

Thus, the final sample includes six years (2002-07) before the crisis, and a nine year crisis

`sufficient-to-create-security-interest`.
If the titled property is inventory meant for sale, a UCC filing is required.

[19] List of largest lenders in the sample available in Appendix A4

and recovery period (2008-16) with a total of 995,657 new loan originations in the period.

Collateral Information As described above, UCC filings are made for all non real-estate, non-titled personal property of borrowers. Figure A2 gives an example of a typical UCC filing. The filing includes information on the borrower (Best Dedicated LLC located in Kernersville, North Carolina), the lender (Webster Capital Finance Inc), the date of the filing (8/12/2014), and a description of the collateral (in this case, trailers) pledged.

There is large variation in the type of collateral pledged for loans, a fact which is going to be critical for my identification strategy. For example, collateral can vary from very specifically identified assets (as in the example above which identifies assets by their serial numbers) to blanket liens. Detailed examples are provided in Appendix Section A3.4.

Blanket liens occur commonly in collateral descriptions. A blanket lien is a lien that gives the lender rights to seize all assets of the borrower in case of default. As such, these statements contain generic descriptions of the collateral. A typical blanket lien reads as follows:

> *"all assets of debtor wherever located and whether now owned or existing or here after existing or acquired including, but not limited to, the following: all accounts, accounts receivable, furniture, machinery and equipment, inventory, goods in process, goods, contract rights, documents of title, chattel paper, letter of credit rights and instruments, general intangibles, instruments, documents, all returned goods and repossessions and replacements thereof, deposit accounts, cash, cash equivalents, investment property, all attachments, accessions, accessories, fittings, increases, tools, parts, repairs, supplies and commingled goods relating to any of the foregoing and all products, substitutions, renewals, improvements, replacements, and proceeds of any of the foregoing, and all books, correspondence, credit files, records, invoices and other papers and documents, tangible or electronic, relating to the foregoing, and to the extent so related, all rights in, to and under all policies of insurance, including claims of rights to payments thereunder and proceeds therefrom, including any credit insurance"*

As such, blanket lien descriptions do not provide sufficient information about the exact assets of the borrower, which is crucial for my measure and identification strategy. Thus, I remove from the sample loans with blanket lien pledges. My sample retains firms with real assets where an exact description of the asset is available. Appendix Section A5 includes additional results comparing firms with blanket liens (or cash-flow pledges) to firms that pledge real assets.

2.1.3 Longitudinal Business Database

For real outcomes at the firm-level, I use information from the U.S. Census Bureau, specifically the Longitudinal Business Database (LBD). The LBD contains annual data (as of March 12) on establishment level employment, payroll, industry, location, and years of operation for the universe of non-farm employer firms in the U.S.

The LBD is the most comprehensive and accurate source of firm-level employment available in the U.S. and contains time-invariant establishment identifiers to track changes in outcomes over time. The database covers both single-establishment and multi-establishment firms. A firm-level identifier tracks the various establishments operated by a single legal entity.[20]

Finally, I aggregate the establishment-level data to the firm-level to track the effects of credit access on firm employment. The majority of the sample ($\sim$ 92%) is single-establishment firms. For firms with multiple establishments, I take the firm county (industry) as the county (industry) with the highest employment share of the firm.

2.2 Matching

To track the relation between firm credit and employment outcomes, I link the loan data from UCC filings to the LBD. With no common identifiers between the UCC Filings and the Census data, I use a fuzzy match based on firm names. To improve the accuracy of the matches, I focus on fuzzy name matching within a ZIP code, i.e., I look for the closest name match among all firms in the borrower's ZIP code. I use a combination of bigram string

[20]FIRMIDs are generated from Employer Identification Numbers (EIN) in tax forms. Thus, a firm is a set of establishments under the same tax filing unit. A single large firm may have multiple EIN numbers. This is less of a concern for small businesses.

comparators to aid with the matching.[21] Through my matching algorithms, I am able to match roughly 52% of the total loans. The match rate over time is provided in Figure A1.

There are multiple reasons for unmatched firms in the original sample. First, the LBD only contains employer firms.[22] Thus, non-employer firms with outstanding loans cannot be matched to the LBD. Non-employer firms constitute account for nearly 23 of the 28 million establishments in the U.S. However, though this subset may be large, it is of less importance when studying the effect of credit access on firm and aggregate employment outcomes. In unreported results, I show that the lending results are robust to including the entire sample of firms. Second, firms operating under multiple names might generate low match scores. Third, to avoid spurious matching, I use a conservative matching restriction. Thus, combinations that generate a low score are dropped, leading to lower match rates than with manual matching techniques that could better discern matching accuracy. The large sample at hand prevents manual inspection of all generated matches. I thus err on the conservative side. Further detail on the data cleaning and matching are provided in Appendix A3.

The final matched sample includes 93,000 non-FIRE firms and roughly 486,000 loans between 2002 and 2016. Comparison of the full Census data to the matched UCC lending - Census data is provided in Table A1. On average, the matched sample is larger (70 employees in matched sample vs. 25 employees in the average firm) and older (13.6 vs 10.6 years in operation).

In this matched sample, 44,500 firms have at least one loan between 2002 and 2007 (pre-crisis period). Of these, 23,500 firms have loans with real assets pledged as collateral. These 23,500 firms, therefore, constitute my baseline sample. Summary statistics on the baseline sample are provided in Panel A of Table 1. The average firm has operated for 12.73 years as of March 2007, with 14.12 employees in that year.

[21]See COMPGED and SPEDIS functionality in SAS

[22]Non-farm payroll employment excluding non-profit organizations

3 Collateral Match Quality

The goal of this paper is to identify whether differences in level of firm-lender collateral match affect firm access to credit in the event of a credit supply shock. Specifically, I study how specialization of a lender in the assets of the firm can affect firm outcomes. In this section, I formalize what I mean by collateral match and lender specialization and how I construct these measures.

In principle, I want to estimate the collateral that a lender is specialized in and measure how a borrower's collateral compares to the specialization of the lender. My measure relies on the theoretical literature (Winton (1999), Dell'Ariccia, Friedman, and Marquez (1999)) that suggests that lender's concentration in a sector implies expertise. In these models, because lenders have more interaction with borrowers in sectors in which they have a greater exposure, they are better informed about these sectors. Similarly, under my measure, borrowers with collateral more in line to what the lender traditionally accepts (controlling for aggregate availability of the collateral in the economy), would imply a better match on collateral.

I create the measure of firm-lender collateral match by examining the textual similarity between the borrower's collateral and the collateral accepted by the lender. To create the measure, I translate the text descriptions into a numeric equivalent and compare two descriptions using the cosine similarity measure. I describe each of these steps in detail below.

3.1 Text to Numeric Conversion

First, I translate textual descriptions of collateral into a numerical format suitable for analysis. I start by aggregating the collateral description for each loan filing and cleaning collateral descriptions.[23] Next, I create a dictionary of all words in the universe of collateral descriptions. I manually inspect the list to retain words that describe the collateral while removing extraneous descriptive words.[24] To retain loans/firms with real assets, I create a dictionary of

[23] I remove punctuation, special characters, extra spaces, and numbers (like serial numbers of equipment) from the description. Furthermore, I remove stop words (most common words that occur in the English language).

[24] For example, common words in collateral description include "proceeds", "limited", "including' which do not add additional information about the assets are removed.

words for all real assets (equipment and machinery) from my sample, and retain descriptions with just these words. Appendix A4 contains the full list of words.

The words are then transformed into a matrix of features (in my case, collateral types) using a "bag of words" approach. Each description is represented as a vector where the ith component takes a value of one if the ith feature is present, and zero if not.[25] Vectors are adjusted by feature weights across documents, i.e., the inverse document frequency (IDF). The IDF captures how common a given word is in the overall sample of loans. Scaling by IDF prevents the overweighting of common terms. The idea behind IDF is to provide higher weights to words with more information. Collateral that occurs rarely provides greater information about a lender's specialization if present in it's portfolio. In my case, the weighting controls the aggregate availability of the collateral in the economy.

To understand the importance of weighting in my case, consider the following hypothetical example. Lender A's portfolio consists of 10% loans against cattle and 10% loans against tractors. Overall in the economy, only 1% of loans are made against cattle while 20% of loans are made against tractors. Without the weighting, the collateral match between a borrower with tractor to Lender A would be identical to the collateral match between a borrower with cattle and Lender A. However, the disproportionate share of cattle in Lender A's portfolio compared to the economy implies Lender A has greater specialization in cattle than the average lender in the economy. The weighting captures this effect.

To formalize, for each word w in collateral description c in the universe of collateral descriptions C, I create

$$\text{TFIDF}_{cw} = TF_{cw} \times IDF_{Cw}$$

where TF_{cw} takes the value 1 if the firm has the type of collateral and 0 if it does not, and

$$\text{IDF}_{Cw} = \log \frac{N}{|c \in C : w \in c|}$$

[25]The baseline measure does not include weighting by term frequency (TF), i.e., the number of times a term appears in a given description. Collateral descriptions very often repeat terms to describe the claims on the same asset. Thus, weighting by TF could lead to over weighting firm assets. I ensure results are qualitatively similar when including the weighting.

which is the log of the total number of collateral descriptions scaled by the number of descriptions where the term w appears

3.2 Cosine Similarity

Next, I use the concept of cosine similarity[26] to calculate the match quality on collateral between borrowers and lenders. Technically, with each description represented in the vector space as described above, similarity between two descriptions can be calculated as the cosine of the angle between the two vectors. This commonly used measure follows from the Eucledian dot product formula

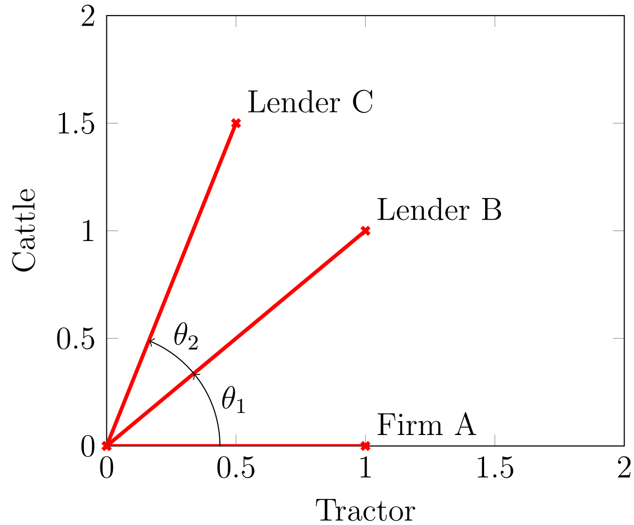
$$\text{Similarity} = cos(\theta) = \frac{\vec{A} \cdot \vec{B}}{\|\vec{A}\| \, \|\vec{B}\|}$$

To create my measure of collateral match between Firm A and Lender B, I compare the collateral of firm A to the collateral of the average borrower of lender B.

The intuition underlying cosine similarity is the idea that two descriptions are similar if their vectors "point" in the same direction. It is a measure of orientation rather than magnitude. This is advantageous when comparing collateral descriptions of varying lengths. Descriptions with the same set of words in the same proportion will have similarity of one and descriptions with no common words between them will have a similarity of zero. In this aspect, cosine similarity performs better than standard measures such as Euclidean distance when high dimensional, sparse matrices are present.

To better understand the intuition, consider a simple example. Think of a universe with just two types of collateral - cattle and tractors - in equal proportion. In this world, every firm and lender can be represented in a two-dimensional space.

[26] Previously used in the finance literature to measure industry similarities in Hoberg and Phillips (2010) and Hoberg and Phillips (2016) and to calculate the impact of patents in Kelly, Papanikolaou, Seru, and Taddy (2018).



A firm with only tractors (Firm A) is on the X-axis. Lenders with both tractors and cattle can also be represented in the two-dimensional space. Consider two such lenders - Lender B (with 50% tractor and 50% cattle) and Lender C (25% tractors and 75% cattle). To measure the match quality (similarity) between a firm and lender, I calculate the cosine of the angle between the two vectors. The angle between Firm A and Lender B is smaller than Firm A and Lender C. A smaller angle implies greater "similarity" in collateral, or in other words, a better match on collateral. In this example, Firm A has a better match to Lender B than it does to Lender C.

I calculate the match quality at the firm-lender level as the cosine similarity between the firm and the average borrower of that lender in the sample. Measures are all calculated based on loans originated in the pre-period (2002-07). To construct the measure, I use information on real assets pledged by the borrower to its relationship lender, and compare that to the average borrower of its relationship lender.

Statistics on the firm-lender collateral match quality values are provided in Panel B of Table 1. The average match quality between firms and lenders on collateral for observed firm-lender pairs is 0.3827 with a standard deviation of 0.3085. The 10th percentile of the distribution is 0.01649 and 90th percentile is 0.8619.

4 Empirical Methodology and Results

4.1 Empirical Strategy

I study the effect of differences in level of collateral match between borrowers and lenders in determining credit supply to firms in the aftermath of the financial crisis. I am interested in understanding whether lenders treat borrowers differentially based on the collateral available at the firm and the level of matching between borrowers and lenders on collateral. Broadly speaking, a drop in credit to firms following the financial crisis could be driven either by lower firm demand, or a decrease in supply of credit to firms. Under the demand side explanation, firms that received fewer loans did so because they lowered their demand for credit. Under the supply side argument, decrease in lending to firms could be driven by the characteristics of the firm, or differences in firm collateral. I aim to isolate the credit supply channel, specifically the role of collateral, in determining firm credit access.

To estimate the causal effect of borrower lender collateral match on credit supply, I follow a difference-in-difference strategy with continuous treatment intensity. I measure a firm's treatment intensity based on the level of matching between a borrower and lender using collateral pledged by the firm to the lender in loans extended to it in the pre-crisis (2002-07) period. I then study the effect of the firm's collateral match to its lenders on credit access in the downturn.

I first document the role of collateral in observed matching between borrowers and lenders. I show that the equilibrium observed borrower and lender pairs are highly concentrated in the top decile of the distribution of random borrower-lender collateral match scores. Furthermore, there is heterogeneity in level of matching across borrower-lender pairs. My tests rely on exploiting the heterogeneity in these match scores.

Given non-random matching between borrowers and lenders, endogeneity concerns due to self-selection arise. Specifically, we are concerned that borrowers that have better matches to lenders may be unobservable different from borrowers with weak lender matches. Similarly, lenders who lend to borrowers that possess collateral in which the lender has greater expertise may be different from lenders who make loans to borrowers outside of their specialization.

To address the identification concerns, I focus on differences in lending behavior to borrowers of the *same* lender, and lenders of the *same* borrower. That is, I estimate the effect of matching on collateral within borrowers and within lenders. The aim of the within-firm regression (see for example Khwaja and Mian (2008), Gan (2007), Schnabl (2012), Jiménez, Ongena, Peydró, and Saurina (2017)) is to control for unobservable differences across firms. Through this approach, I test the effect of collateral matching independent of inherent differences across borrowers and lenders. Conditional on having borrowed from a given set of lenders in the pre-crisis period, I test the post-crisis change in lending to the *same* firm from lenders with differential levels of collateral match.

I then try to disentangle other potential channels driving lender behavior. Specifically, I want to establish two facts. First, I aim to show that differences in lending are driven by collateral specialization and not other potential lender advantages such as knowledge about the industry, or firm-specific knowledge. Second, I try to disentangle the channels driving specialization of lenders. Broadly speaking, lender specialization can be driven by informational advantages about the collateral, or the lender's concerns about potential losses incurred on loans. I argue informational advantages about the collateral push lenders to specialize in a downturn.

After establishing the importance of collateral matching for lending outcomes at the firm-lender level, I proceed to test the effect of matching at the firm-level. I study the effect of credit from pre-existing relationship lenders of the firm. Furthermore, I study the ability of firms to substitute to new lenders, and the total credit available to the firm. Finally, I focus on the differences in firm-level employment growth.

Below, I present each of these results in detail.

4.2 Firm-Lender Level Results

I start by documenting the importance of collateral match for lending outcomes. First, I provide evidence for matching between borrowers and lenders based on collateral specialization of lenders. For this, I plot in Figure 1a two distributions. In the solid line, I plot the firm-lender collateral match scores for all possible firm-lender pairs. That is, for every firm in my sample, I create a measure of collateral match to every lender in the sample (irrespective of whether they actually borrow from them). To create the measure, I use the pre-crisis (2002-07) collateral pledged by the borrower and compare it to the pre-crisis lending portfolio of the lender. The solid line, therefore, is the distribution of collateral match scores for a random firm-lender match. Note that the distribution is highly skewed with most of the distribution concentrated at near-zero values of collateral match. In the dashed-line, I plot the same firm-lender collateral match scores for equilibrium observed matches of firm-lender pairs (firm-lender pairs with a loan in the pre-crisis period). We note that the observed firm-lender pairs have a greater match on collateral than would be implied by a random matching. Specifically, nearly half the observed firm-lender pairs are in the right 5% tail of the distribution of random scores. This provides suggestive evidence that collateral, and lender specialization in collateral is an important determinant of firm credit.

In this paper, I am interested in how the level of matching between firms and lenders affects change in lending a downturn. For this, I focus my analysis on the second big takeaway from the plot, i.e. the heterogeneity in match scores across observed borrower-lender pairs. I exploit this heterogeneity to identify distribution of credit across borrowers in a downturn.

Figure 1b plots the distribution of firms receiving loans in the pre- and post-crisis periods. In the solid line, the Firm-Lender Collateral Match Quality for the full set of firm-lender pairs with at least loan in the pre-crisis period is plotted. In the dashed line, I plot the distribution of scores for the set of firm-lender pairs within that sample that also get a loan after 2008. Notice that the distribution for firms receiving repeat loans is shifted to the right.

Figure 2 plots lending over time for firm-lender pairs with a relationship between 2002 and 2007. Firm-lender pairs are divided into two groups with above and below median scores on firm-lender match quality score. We see that lending to the two groups grow along similar paths in the pre-crisis period. After the start of the crisis, however, growth of loans between the two groups diverge. Firms with closer match to the lender see a smaller drop in lending during the crisis, and the gap between the two groups persists post-crisis.

However, as described above, this result is prone to endogeneity concerns. Thus, I plot two additional figures. In Figure 3a, I split lenders to the same firm into above and below median match scores. That is firm-lender pairs are classified as above or below median within firm. The sample here is restricted to firms with multiple relationships pre-crisis. As above, lending to the firm from the two groups of lenders grows on a similar path pre-crisis but diverges after the start of the crisis. Similarly, in Figure 3b, I separate firm-lender pairs into above and below median match quality within the same lender, i.e. borrowers with high vs. low match to a given lender. Observed lending patterns are similar with this categorization.

I now turn towards establishing this result more formally through regression analysis. My main empirical specification is as follows:

$$\text{Repeat Loan}_{fl} = \alpha_f + \gamma_l + \beta_{\mathbf{1}}\text{Firm-Lender Collateral Match Quality}_{fl} + \epsilon_{fl} \qquad (1)$$

for every firm f, lender l with a pre-existing relationship in the pre-crisis period. The outcome variable takes value of 1 if the firm gets a new loan from the same lender in the post-crisis period. Since all firm-lender pairs have a loan between them ex-ante, repeat loan captures the change in lending to the firm. The main variable of interest is the measure of Firm-Lender Collateral Match Quality created based on pre-crisis loans. The measure captures the level of matching between the borrower's collateral and the collateral of the lender. The baseline specification also includes borrower and lender fixed effects to study the change in lending *within* the same firm across different lenders, as well as change in lending across borrowers of the *same* lender.

Table 2 presents the results of the baseline specification in Equation 1. Column 1 presents the results for all firm-lender pairs observed in pre-crisis period. A one standard deviation increase in the match quality to lender increases lending by 2.04% equivalent to 10.3% of the mean. In column 2, I include controls for county and industry[27] of the borrower to control for differences in demand. The effect changes increases to 2.41% for a one standard deviation increase in match quality. In Column 3, lender fixed effects are included to control for lender-level variation in specialization and lender level differences in borrower matching. This increases the effect to an increase in probability of getting a repeat loan by 2.56%. Including lender fixed effects, local county-industry demand, and firm controls in column 4 leaves the effect almost unchanged at 2.53% increase in loan probability for a one standard deviation increase in match quality.

[27]For multi-establishment firms, county is the assigned based on the region with highest employment share for the firm. Industry at 2-digit NAICS level but robust to narrower industry definitions.

In Columns 5-7, I restrict the sample to firms with multi-banking relationships in the pre-crisis period. Column 5 repeats the results of Column 3 for multi-relationship firms. We see the effect is slightly larger for this sample with a one standard deviation increase in collateral match leading to a 3.36% increase in lending, equivalent to 16.2% of the unconditional probability of getting a repeat loan. Including firm fixed effects in Column 6 implies a one standard deviation increase in match quality leads to 3.27% increase in repeat lending. That is, a one standard deviation increase in match quality between lender and borrower increases lending to the same firm by 3.27%. Finally, the last column includes both firm and lender fixed effects. Here, a one standard deviation increase in firm-lender collateral match quality increases lending to the firm by 3.7%, or 17.85% of the mean and 9.13% of the standard deviation, the headline result of this paper.

Dynamic Difference-in-Difference

Next, I test for dynamic effects of firm-lender collateral match on lending. Specifically, I run the following regression:

$$\mathbf{y}_{flt} = \alpha_f + \gamma_l + \delta_t + \beta_t \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \epsilon_{fci} \tag{2}$$

where for each firm f, lender l pair with a loan in the pre-crisis period, I test for change in lending each year t. The dependent variable is an indicator that takes value of one if the firm-lender pair is observed to have a loan in a given year, scaled by frequency of loans between the pair in the pre-crisis period. I scale the loans for a measure of percentage change in lending given the data limitation of only observing extensive margin of loan originations. I am interested in the variation in the coefficient on firm-lender collateral match over time.

The dynamic version of the difference-in-difference setting serves to identify the timing of the effect of firm-lender collateral match on loan outcomes, and to establish the existence of parallel pre-trends which is crucial for my identification strategy.

Results are presented in Table 3. I note that, including relevant controls in Column 3, there are no statistically significant differences in lending across firms with different levels of firm-lender collateral match in the pre-crisis period. However, after the start of the financial crisis, firms with high quality match are more likely to get a loan. The effect persists for a few years before recovering to pre-crisis levels in 2016. The magnitude of the effect is highest in 2008 with a one standard deviation increase in match leading to an increase in scaled lending of 18.4% to all firms (Column 3) and 6.82% for multi-relationship firms (Column 4).

4.2.1 Other Specialization Channels

Next, I aim to disentangle whether the observed results are truly driven by expertise in borrower collateral. Potentially, lenders could have borrower-specific advantages beyond expertise in collateral. Lenders could be specialized in the industry of the borrower, with an informational advantage over borrowers in certain industries versus others. Lenders could also have firm-specific knowledge. They may have borrower-specific information gathered through past relationship with the lender. Such expertise may help them distinguish good borrowers from bad, and could be the underlying mechanism driving observed lending behavior. I test for these alternate specialization channels below.

Industry vs. Collateral Specialization

First, I test for lender specialization in the borrower's industry. Here, I analyze whether the observed lending patterns are driven by the collateral of the borrower or the industry of the borrower. To be clear, collateral and industry specialization may greatly overlap. Borrower collateral is largely driven by the industry in which the firm operates, for example - farmers often use tractors while restaurants do not. However, oftentimes, collateral could be more broad or more specific than industry definitions. On the one hand, certain types of collateral are used across multiple industries (e.g. forklifts and trucks). On the other hand, lenders may specialize in lending only against certain types of collateral even within an industry. As an example, People's United Bank's equipment financing division makes loans against large service trucks but not usually against delivery or utility trucks.[28]

To separate lender specialization in an industry from its collateral specialization, I con-

[28] https://www.peoples.com/business/equipment-finance/peoples-united-equipment-finance-corporation/transportation

duct two tests.

$$\text{Repeat Loan}_{fli} = \alpha_f + \gamma_l \times \delta_i + \beta_1 \text{Firm-Lender Collateral Match Quality}_{fl} + \epsilon_{fl} \tag{3}$$

for firm f, in industry i, borrowing from lender l, I include lender times industry fixed effects to compare treatment of borrowers within the same lender and the same industry. The sample is once again firm-lender pairs with a pre-existing relationship in the pre-crisis period. The outcome variable takes value of 1 if the firm gets a new loan from the same lender in the post-crisis period.

Panel A of Table 4 presents results these results. I present the effect with 2-digit and 3-digit industry cells in Column 2 and 3 of the table. We see that including the industry interactions changes the magnitude of the effect on likelihood for getting a repeat loan from 3.7% to 4.1% with 2-digit industry fixed effects and to 4.13% with 3-digit industry fixed effects. Collateral match, therefore, is still a significant determinant of credit to borrowers.

Ideally, we are interested in narrow industry specialization of lender. Including very narrow industry fixed effects significantly decreases sample size. Thus, in alternate tests, I include instead of lender-industry fixed effects, lender concentration by industry. I calculate lender concentration for narrow industry cells as the share of lending to that industry in the lender's portfolio.

Panel B of Table 4 presents these results. I include lender concentration at the 2,4, or 6 digit NAICS level. Including lender share in industry changes the magnitude of a one standard deviation increase in firm-lender collateral match quality to 3.54% across the specifications. That is, industry specialization does not seem to explain away the observed lender collateral specialization.

Hard vs. Soft Information

Next, I test for whether lender behavior is driven by firm-specific knowledge. Lenders may collect firm-specific soft information through lending relationships. Change in lending could, therefore, be driven by such firm-specific soft information rather than borrower collateral. To test for this, I conduct two tests.

First, I include proxies for relationship strength as controls in my baseline regression. I create three proxies for strength of relationship - 1) Number of past loans from the lender, 2) share of total borrower lending from the lender, 3) time since the last loan between the borrower and lender and the start of the crisis. An increase in number of loans from the lender implies the lender has had greater interaction with the borrower, increasing the potential information the lender has about the borrower. Conversely, if a longer time has passed since the last loan to the borrower, the lender may have less up-to-date information about the borrower.

These measures proxy for soft information, but may themselves be correlated with higher collateral match. For example, lenders may be willing to make a greater number of loans to borrowers whose collateral they understand. Thus, I believe, adding these controls may downward bias the true effect of the importance of collateral matching. The results shown in Table 5 are, therefore, a conservative estimate for the effect of collateral match quality.

As shown in Table 5, including the controls for relationship lending decreases the magnitude on the coefficient of interest. In Column 1, I repeat the results from the baseline regression. Here, a one standard deviation increase in firm-lender match quality increases lending to the borrower by 3.72%. In Column 2, I use share of lending from the relationship lender as a control for relationship strength. Compared to the baseline regression, the effect here reduces to 2.29% increased loan likelihood, or 11% increase over the mean loan likelihood. In Column 3, I include a measure of the average annual number of loans between the borrower and lender in the pre-crisis period. This decreases the effect to 10.1% above the unconditional mean of repeat loan . In Column 4, I include, as a control, the number of years since the last loan to the borrower. The effect of match quality in this case is equivalent to a 14.87% increase over the mean. Finally, I include both the number of loans and time from the last loan as a control. The final effect is a 2.1% increase in loan likelihood, or 10.1% over the mean value. Thus, even though the inclusion of these controls reduces the magnitude of the effect on collateral match quality, lender match is still an economically significant determinant of firm credit.

For the second test of importance of private firm-specific information, I test the importance of match on collateral for *new* borrowers of the lender. For firms with no prior-relationship, the lender does not possess private firm-specific information. As shown in Figure 4, the observed matches for borrowers with loans in the post-crisis period is significantly higher than would be implied by a random firm-lender pair match. This provides evidence for non-random matching between borrowers and lenders on collateral, conditional on the lender *not* having any borrower-specific private information. Thus, collateral is an important determinant of credit.

4.2.2 Mechanisms for Specialization

Next, I try understand the channels driving lender specialization in a downturn. Specifically, lenders could be specializing for multiple reasons. First, lender specialization may be driven by informational advantage. Lenders could have ex-ante private asymmetric information about the quality of collateral (ability to identify good collateral from bad), or possess greater ability to redeploy the collateral ex-post (which may include existing infrastructure for collateral storage and disposal, network of potential buyers etc.). Informational advantages may cause a lender to specialize in core collateral when in distress.

Second, lending behavior could be driven by the type of business the lender is involved in. Traditionally, banks are thought to do more cash-based lending (evaluate firms based on project cash flows) while finance companies lend against asset values (Carey, Post, and Sharpe (1998)). For some lenders in the sample, example captive finance companies, collateral sales and value may be primary motivation for lending. In this case, one could be worried that concentration of lenders is driven by need to increase parent company sales and collateral value. Thus, observed behavior of change in lending against collateral could be driven by differences in underlying businesses.

Third, lenders may concentrate borrowing to prevent writing down of bad loans, i.e. zombie lending (Caballero, Hoshi, and Kashyap (2008)). Distressed banks may reallocate credit to borrowers most likely to lead to loan losses if cut-off. If the firm-lender collateral measure captures the level of prior investment or commitment of the lender, they may be inclined to continue lending to borrowers with higher match to prevent losses on their portfolio.

Fourth, lenders may be worried about fire sales losses (as in Shleifer and Vishny (1992)).

Lenders may therefore concentrate their portfolio on assets less likely to face fire sale discounts in case of default. In this case, lenders would concentrate lending on the most common assets in the economy which are likely to be most liquid and least prone to fire sale losses. If, on average, lenders are less specialized in uncommon assets, a shift to core assets would line up with a concentration in most common assets in the economy, driven by concerns about fire sale losses.

In this paper, I want to argue that lender specialization is driven by informational advantage. While I cannot directly test for the amount of information about collateral available to the lender, I try to eliminate the other potential channels described above.

Heterogeneity Across Lenders

First, I test for whether differences in underlying business of the lenders drive observed variation in lending. To test for variation across lenders, I include indicators for lender type in my baseline specification.

$$\begin{aligned} \text{Repeat Loan}_{fl} = \alpha_f + \gamma_l + \beta_1 &\text{Firm-Lender Collateral Match Quality}_{fl} \\ &+ \beta_2 \text{Firm-Lender Collateral Match Quality}_{fl} \times \text{Lender Type}_l + \epsilon_{fl} \end{aligned} \tag{4}$$

Primarily, I test three main theories for specialization. First, I test for whether results are driven by the subset of lenders in my sample that are only concerned about collateral values. Lenders such as finance companies who lend primarily against collateral value of the borrower could be the one shifting focus in times of distress while traditional lenders such as banks lend to borrowers based on cash-flow evaluations. If that were the case, borrowers of finance companies would be affected while banks do not alter behavior based on collateral. In Column 1 of Table 6, I show that there is no statistically (or economically) significant difference across banks[29] and non-banks in their behavior.

Second, results may be driven by lenders whose primary business is not small business lending. Specifically, captive finance companies, who are lending arms of manufacturing companies, may be interested in increasing asset sales and propping collateral value to benefit the parent company. These companies may increase lending to, in turn, increase parent

[29] Commercial banks, non-bank subsidiaries of bank holding companies, and credit unions.

company revenue. As these lenders are also on average more specialized, greater lending from better firm-lender collateral matches could be driven by increased lending from captive finance companies. I test if this is case. I would like to point out, however, that captive finance companies also have informational advantage over other lenders in the economy. Specifically, captive finance companies have greater information about the true quality and resale value of the collateral due to close association with the producer of the good. Thus, difference across captive finance companies and other lenders could be driven by either channel. However, the goal is to check whether shift in lending is driven only by lenders whose primary goal is asset sales. In Column 2 of Table 6, I interact the firm-lender collateral match quality measure by an indicator for captive finance companies. The effect of increase in collateral match on lending is significantly higher for captive finance companies. A one standard deviation increase in match quality increases lending by 3.85% for non-captive lenders and 10.18% for captive lenders.

Third, I test for differences driven by large banks. As shown in Chen, Hanson, and Stein (2017), the largest 4 commercial banks pulled out of lending to small businesses in the aftermath of the financial crisis. If large banks are less specialized (more diversified) and pull out, the average continued firm-lender pair would appear to be better matched on collateral. I test for this in Column 3 of Table 6. There appears to be no statistically significant difference across Top4 banks and other lenders in the sample.

Zombie Lending

Next, I test for the existence of zombie lending. In a downturn, lender decisions may be driven by need to prevent loan losses. Lenders, to prevent writing down bad loans, may continue making loans to bad borrowers. If firm-lender collateral match captures the extent of the lender's exposure in the borrower's business, lenders have more to lose by cutting off lending to borrowers they are better matched to. Thus, they may be inclined to continue lending to such borrowers.

To test for presence of zombie lending, I compare lending behavior of banks based on their financial strength. Theories would indicate that zombie lending should be more pronounced for lenders who are capital constrained. Under-capitalized banks are more likely to engage in zombie lending behavior. Thus, I split my banks into above and below median capitalization based on Tier 1 Capital Ratio of banks as of December 2006. I test for differences across the two sets of banks through the following specification:

$$\begin{aligned} \mathbf{y}_{flt} =& \alpha_{fl} + \delta_t + \beta_{1t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \\ & \beta_{2t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t \times \text{High Capital}_l + \epsilon_{fci} \end{aligned} \tag{5}$$

where for each firm f, lender l pair with a loan in the pre-crisis period, I test for change in lending each year t. The dependent variable is an indicator that takes value of one if the firm-lender pair is observed to have a loan in a given year, scaled by frequency of loans between the pair in the pre-crisis period. I scale the loans for a measure of percentage change in lending given the data limitation of only observing extensive margin of loan originations. I am interested in the variation in the coefficient on firm-lender collateral match interacted with lender capitalization over time.

Results can be visualized in Figure 8. I show that there is no statistically significant differences in specialization across lenders with high and low Tier 1 capital. The point coefficients, through insignificant, are positive, inconsistent with the zombie lending hypothesis. Coefficients are presented in Appendix Table A5.

Fire Sales

Finally, I test for whether fire-sales concerns drive lender behavior. Here, the concern is that lenders shift lending towards the types of collateral that are least likely to face fire sale discounts when a borrower defaults (i.e. most common / redeployable collateral). If all lenders have a lower initial concentration of illiquid collateral in their portfolio, a shift to liquid collateral will appear to be a shift towards collateral they specialize in. Thus, I test for whether fire sale concerns drive lender behavior.

To test the existence of fire sales, I test differences in lending by industry performance. Theories of fire-sales indicate that fire-sale discounts are highest when other potential buyers of the collateral are in distress, and when inside users (buyers in the same industry) are unable to buy the collateral. Therefore, fire sale discounts would be highest for distressed industries. Thus, if lenders are worried about potential fire sale losses, even a high firm-lender collateral match would not be sufficient to persuade a lender to lend to the borrower in a distressed industry.

$$\begin{aligned}\text{Repeat Loan}_{fli} &= \alpha_f + \gamma_l + \beta_1 \text{Firm-Lender Collateral Match Quality}_{fl} \\ &+ \beta_2 \text{Firm-Lender Collateral Match Quality}_{fl} \times \text{Industry Performance}_i + \epsilon_{fl}\end{aligned} \tag{6}$$

for firm f in industry i borrowing from lender l. I measure industry performance as the weighted average change in employment around the financial crisis for all firms in the borrower's industry.[30]

Results are presented in Table 7. Columns 1,2,3 show the effect of firm-lender collateral match interacted with performance of the industry at the 3-digit, 4-digit, and 6-digit NAICS level. I show that there is no statistically significant effect of collateral match by performance of the industry on lending. These results suggest that fire-sales concerns are not the main driver of lender specialization.

4.2.3 Counter-factual Exercise

I use the results from the within-firm regressions to study the aggregate effects of lender matching on loan supply. I follow a strategy similar to Chodorow-Reich (2013) and Acharya, Eisert, Eufinger, and Hirsch (2018) to estimate the aggregate effect. For each borrower-lender pair, I estimate the counter-factual loan supply if the firm and lender were aligned on collateral. Specifically, I estimate the additional credit to the firm if the lender had been specialized in the borrower's collateral.

I consider the effect of change in matching to a lender under two different conditions. First, I consider the highest possible firm-lender match score given the collateral the borrower pledged to the lender. In other words, for every firm-lender pair, I take as given the collateral pledged by the borrower to the lender. With this collateral, I estimate the match scores to all other lenders in the sample. The best match for the borrower is the firm-lender

[30] Measured here as change in employment in a three year window around the financial crisis - i.e. change in average level between 2005-07 and 2008-10. Result insensitive to the choice of the time period. Lack of balance sheet information for small businesses prevents the calculation of other industry performance measures for this sample.

collateral match that generates the highest score for the given collateral. Second, I consider improvement in lending under hypothetical scenario where specialized lenders exist for all borrowers. That is, I take the highest value, the 95th and 90th percentile of the firm-lender collateral match score distribution. In this case, I estimate the increased lending to the borrower under the hypothetical scenario where a lender specialized to the same extent in the borrower's collateral is available.

I use a partial equilibrium analysis to determine the aggregate effect. Under the assumption that total lending is the sum of lending to individual firm-lender pairs, I can estimate the effect as follows:

$$\tilde{y}_{fl} = \hat{y}_{fl} + \beta_1 \times [\widetilde{\text{FLSim}}_{best} - \text{FLSim}_{fl}] \tag{7}$$

where $\hat{y}_{fl}$ denotes the fitted value from the regression in Equation 1. $\widetilde{\text{FLSim}}_{best}$ is the counter-factual level of firm-lender similarity on collateral. In the baseline case, this value is 1 indicating perfect match in collateral between the borrower and lender. FLSim_{fl} is the observed value of level of firm-lender collateral similarity. β_1 is the estimated coefficient from Table 2 Column 7.

$\tilde{y}_{fl}$ provides the estimate of loan supply conditional on change in only the level of firm-lender matching keeping all else equal.

The total lending in this counter-factual case is calculated by summing loan supply to each firm-lender pair as follows:

$$\sum \tilde{y}_{fl} \tag{8}$$

To estimate the gain from the shift in lender matching, I estimate the change in lending from the counter-factual lender matching scaled by the observed level of lending in the economy, or

$$\frac{\sum[\tilde{y}_{fl} - \hat{y}_{fl}]}{\hat{y}_{fl}} \tag{9}$$

The results are provided in Table 8. If borrowers changed match to the most specialized lenders for their collateral, total lending to multi-relationship firms would increase by 14.76%. On the other hand, if there existed for each borrower, a lender as specialized in its collateral as the most specialized lender, increase would be even higher. A shift in lender matching from the observed values to a counter-factual with perfect matching to the lender increases total lending by 42.67%. If the firm-lender pairs were instead at the 95th percentile of match score, lending would be 31.34% higher. At the lower bound of a match score at the 90th percentile, aggregate lending would still increase by 21.76%.

4.3 Firm-Level Results

Having established the importance of collateral for credit outcomes at the firm-lender level, I trace the impact of collateral match quality for firm outcomes. I create a measure of firm-level collateral match by aggregating the firm-lender collateral match qualities. That is,

$$\text{Firm Collateral Match}_f = \sum_{l \in L} \text{Lender Share}_{fl} \times \text{Firm-Lender Collateral Match}_{fl}$$

based on all relationship lenders l of the borrower f.

4.3.1 Lending

For firm credit outcomes, I first test the impact of firm collateral match on credit to firms from their relationship lenders. In Figure 5a, I plot lending over time to firms with above and below median match on collateral to their relationship lenders. We see that lending to the two sets of firms grows along a parallel path before the start of the crisis. After 2008, firms with better match to their relationship lenders get more credit from them, and this gap persists in the post crisis period.

To control for differences across borrowers with differential collateral match to their relationship lenders, I regress firm credit from relationship lenders on level of Firm Collateral Match, controlling for observable differences across borrowers

$$\text{Repeat Loan}_f = \alpha + \beta_1 \text{Firm Collateral Match}_f + X_f + \epsilon_f \tag{10}$$

Results are provided in Panel A of Table 9. Columns 1-3 present result for the full sample of firms in the sample. In Column 1, without any firm-level controls, a one standard deviation increase in firm collateral match increases lending from relationship lenders by 1.77%. Adding local county and industry fixed effects changes the magnitude of the effect to 2.05%. Finally, in Column 3, I include controls for firm size (log employment as of 2007) and age (log firm age as of 2007). This reduces the effect of firm collateral match to 1.55% for a one standard deviation increase in collateral match. This is equivalent to 5.08% of the mean likelihood of loan from at least one relationship lender.

In Columns 4-6, I focus on the set of firms with multiple pre-crisis relationships. This sample is a direct mapping to the set of firms in my baseline regression in Table 2. For this sample of firms, a one standard deviation increase in firm collateral match increases total lending from relationship lenders by 3.56%, double the size of the effect on the sample of all firms. Adding county, industry controls increases magnitude to 4.42%, and with inclusion of firm size and age controls, the final magnitude of the effect of a one standard deviation increase in collateral match is 3.19% increase in lending, equivalent to 10.35% of the mean and 6.91% of the standard deviation.

Panel B of Table 9 repeats the same test for total firm credit. This includes credit from relationship lenders as well as lending from lenders that the borrower did not have a prior relationship with. Again, I present results for the full set of firms in my sample in Columns 1-3, and for the set of firms with multiple lending relationships in Columns 4-6. The effect of firm collateral match to relationship lenders on total lending is significantly lower than the effect on lending from relationship lenders. In Columns 3 and 6 with all controls included, an increase in firm collateral match has no statistically significant effect on total firm lending.

As noted, the effect of firm collateral match to relationship lenders does not have an economically significant effect on total firm lending. Thus, it appears that firms are able to substitute to new lenders. To test the ability of firms to substitute, I again focus on the collateral of the firm. I create a measure of *Firm Similarity* which compares the collateral of the borrower to the collateral of the weighted average lender in the sample. This measure is analogous to the firm-lender collateral match quality created previously. The difference is that instead of comparing the borrower collateral to its relationship lenders, I now compare it to all lenders in the sample.

In Table 10, I test borrower substitution to new lenders against the measure of firm similarity.

$$\text{New Lender}_f = \alpha + \beta_1 \text{Firm Similarity}_f + X_f + \epsilon_f \tag{11}$$

New Lender takes a value of 1 if the firm gets at least one loan after 2008 from a lender with no pre-crisis relationship.

In Panel A of Table 10, I present the results for substitution. Column 1 indicates that a one standard deviation increase in firm similarity increases the probability of shifting to a new lender by 4.36%. When I include county and 2-digit industry fixed effects, the effect becomes 4.52%. Including controls for firm size and age reduces the effect to 3.44% but still economically significant, equal to 6.56% of the mean probability of shifting to a new lender. In Columns 4-6, I present results by including the firm collateral match to relationship lenders. Better firm collateral match to relationship lenders reduces the probability of borrowing from a new lender by 1.9% in the strictest specification in Column 6.

Finally, I study the effect on total lending against firm similarity. In Figure 5b, I split the sample of firms with above and below median firm similarity. These firms grow at a similar rate in the pre-crisis period. However, in the post-crisis period, firms with above median similarity receive more credit than firms with below median similarity.

Panel B of Table 10 presents effect of firm collateral on total lending. Column 1-3 repeat the results from Panel B of Table 9. In Column 4-6, I include firm similarity as independent variable. A one standard deviation increase in firm similarity increase total lending by 6.01%. This is equal to 9.77% of the mean probability of a loan in the post-crisis period. After including county-industry fixed effects (Column 5) and firm controls (Column 6), a one standard deviation increase in firm similarity increase probability of loan by 5.89% and 5.01% respectively.

4.3.2 Real Effects

In the previous section, I established that firm collateral match affects lending from relationship lenders, while ability to shift to new lenders and total credit to firm is determined by overall firm similarity to the lenders in the economy. Next, I study the effect of firm collateral on real outcomes. I focus on firm employment in this paper.

In Fig 6a and 6b, analogous to credit, I plot firm employment against the two measures of firm collateral - Firm Collateral Match, which is the weighted average of firm-lender collateral match scores to the relationship lenders of the borrower; and Firm Similarity which compares the firm's collateral to the weighted average lender in the sample. To create the figure, I scaled firm employment in a given year by the average level of employment at the firm in the pre-crisis period (2002-07) and average across all firms in the sample. Creating the average this way provides equal weights to small and large firms in my sample, which is important given the focus of this paper on small business outcomes. Notice the dispersion in employment growth across the two groups of Firm Collateral Match and Firm Similarity after the start of the crisis.

To study the effect of lender specialization in collateral on firm employment, I do the following instrumental variable regression.

$$\begin{aligned} \text{Repeat Loan}_f &= \alpha + \gamma_1 \text{ Firm Collateral Match}_f + X_f + \epsilon_{fci} \\ \Delta(\text{Employment})_f &= \alpha + \beta \widehat{\text{Repeat}} \text{ Loan}_f + X_f + \epsilon_{fci} \end{aligned} \tag{12}$$

for the sample of firms f with at least one loan in the pre-crisis period. New Loan takes value of 1 if the firm gets a new loan in the post-crisis period from any lender. I calculate change in employment as the change in average level of employment at the firm between the post-crisis and pre-crisis period as:

$$\Delta(\text{Employment})_f = \frac{\text{Employment}_{f,2008-16} - \text{Employment}_{f,2002-07}}{0.5 \times (\text{Employment}_{f,2008-16} + \text{Employment}_{f,2002-07})} \tag{13}$$

I use the above definition of employment to limit the influence of outliers. The growth rate definition in Equation 13 is a second-order approximation of the log difference growth rate around 0. It lies between [-2,2] and can accommodate exits, which is an important consideration for the sample of small businesses that I study.

Table 11 presents the results for employment. In Panel A, I present the OLS results. A one standard deviation increase in probability of receiving a loan from a relationship lender in the post-period increases employment at the firm by 7.28%. The IV results in Panel B are of similar magnitude at 8.64% growth in employment for one standard deviation increase in new loan. Results are robust to inclusion of county-industry fixed effects and firm controls.

Finally, I estimate a dynamic version of the total ability to borrow against firm collateral on firm employment outcomes. The dynamic version helps establish two broad facts - 1) parallel pre-trends and 2) timing of the change in employment. Therefore, I estimate the following regression:

$$\text{Scaled Employment}_{fcit} = \alpha + \beta_t \text{Similarity}_f \times \mathbf{1}_t + X_f + \delta_{cit} + \epsilon_{fci} \tag{14}$$

where the dependent variable is the level of employment at the firm f in county c, industry i in a given year t scaled by the average pre-crisis level of employment at the firm.[31] I choose scaled level of employment rather than log employment to account for observations of zero employment for firms which may otherwise be dropped. Results, however, are similar on using log values with firm fixed effects.

Results can be visualized in Figure 7. Table A7 provides the results. We see that in the pre-crisis period (2002-07), the employment growth does not vary with collateral similarity with values statistically and economically indistinguishable from zero. However, post 2007, firms with higher similarity have a greater growth rate in employment. Specifically, in 2008, a one standard deviation increase in collateral similarity increases employment by 3.56% above the average level of employment growth. In Columns 2 and 3, I include county times industry and county and industry fixed effects respectively. Again, we notice parallel pre-trends in firm employment before the crisis while they diverge after the crisis. Employment differences converge to similar levels by the end of the sample. While coefficients are not statistically significantly different from zero after 2013, the difference is economically significant up until the end of the sample.

4.4 Aggregate Patterns

The time series patterns on set of borrowers receiving credit can provide more information on the importance of collateral. In this paper, I argue that the reduction in credit supply

[31] Measured as the mean March 2002- March 2007 level of employment

in the aftermath of the financial crisis was associated with a shift towards borrowers with greater collateral match to their lenders. However, this analysis does not clarify how lender behavior varies at other points in time. I shed light on changing lending behavior over time through two tests.

In Figure 9a, I plot the average level of firm-lender collateral match score for the set of firms that receive credit in a give year. The main takeaway from the figure is that in the pre-crisis boom the average level of firm-lender collateral match is lower (and decreasing over time) than the average firm-lender similarity of the set of firms who receive credit in the post-crisis period. After 2007, the firm-lender collateral match is successively increasing till about 2012 after which it stabilizes. This suggests that the level of firm-collateral matching required for credit extension is most important in a downturn.

To identify whether this pattern is driven by just changing composition of lenders and borrowers in the sample, I run the following regression:

$$\text{Loan}_{flt} = \alpha_f + \gamma_l + \delta_t + \beta_t \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \epsilon_{flt} \tag{15}$$

for the set of all firms f and lenders l that receive a loan at any point in my sample. Loan takes a value of 1 if a firm-lender pair is observed with a loan in a given year t. Firm-lender collateral match is calculated based on the full sample (2002-16) of loans. I control for firm, lender, and time differences to test the time varying importance of firm-lender collateral match.

Figure 9b presents the results of the regression in Equation 15. Results are in line with the aggregate results presented - that is, firm-lender collateral match becomes important after the start of the financial crisis while the level does not differentially access to credit in the pre-crisis boom.

5 Conclusion

This paper documents the important role of collateral specialization of lenders for credit supply to borrowers in the aftermath of the financial crisis. Using novel loan-level data on all collateralized loans in Texas between 2002 and 2016 linked to the U.S. Census of establishments, I create a new measure of Firm-Lender Collateral Match Quality to quantify the extent of specialization of a lender in the collateral of the borrower.

By focusing on the set of borrower-lender pairs with pre-existing relationships before the start of the financial crisis, I show that firms that were borrowing from lenders with greater specialization in their collateral are more likely to continue receiving credit after the start of the crisis. This effect is not driven by differences across firms or lenders but holds within borrowers of a lender, and within lenders of a firm. Lender specialization, in turn, affects firm-level outcomes such as total credit and employment.

On exploring the channels leading to lender specialization, I show that informational advantages in collateral are the most likely driver of lender specialization in a downturn. Furthermore, collateral specialization is distinct from other lender advantages that may be industry or firm-specific.

The findings in this paper have important implications for heterogeneous effects of credit supply shocks. I show that the decrease in lending to borrowers of the same lender vary based on borrower collateral. These findings also suggest that not all relationships are equally valuable to a borrower in times of distress, and credit substitution may be limited by lender specialization.

References

Acharya, Viral V., Iftekhar Hasan, and Anthony Saunders, 2006. Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios. The Journal of Business 79, 1355–1412.

Acharya, Viral V., Allen N. Berger, and Raluca A. Roman, 2018. Lending Implications of U.S. Bank Stress tests: Costs or Benefits?. Journal of Financial Intermediation 34, 58 – 90.

Acharya, Viral V., Sreedhar T. Bharath, and Anand Srinivasan, 2007. Does Industry-Wide Distress Affect Defaulted Firms? Evidence From Creditor Recoveries. Journal of Financial Economics 85, 787 – 821.

Acharya, Viral V, Tim Eisert, Christian Eufinger, and Christian Hirsch, 2018. Real Effects of the Sovereign Debt Crisis in Europe: Evidence from Syndicated Loans. The Review of Financial Studies 31, 2855–2896.

Adelino, Manuel, Antoinette Schoar, and Felipe Severino, 2015. House Prices, Collateral, and Self-Employment. Journal of Financial Economics 117, 288 – 306.

Albuquerque, Rui, and Hugo A. Hopenhayn, 2004. Optimal Lending Contracts and Firm Dynamics. The Review of Economic Studies 71, 285–315.

Almeida, Heitor, and Murillo Campello, 2007. Financial Constraints, Asset Tangibility, and Corporate Investment. The Review of Financial Studies 20, 1429–1460.

Ashcraft, Adam B., 2005. Are Banks Really Special? New Evidence from the FDIC-Induced Failure of Healthy Banks. The American Economic Review 95, 1712–1730.

Benmelech, Efraim, 2008. Asset Salability and Debt Maturity: Evidence from Nineteenth-Centure American Railroads. Review of Financial Studies.

———, and Nittai Bergman, 2008. Liquidation Values and the Credibility of Financial Contract Renegotiation: Evidence from U.S. Airlines. Quarterly Journal of Economics.

———, 2009. Collateral Pricing. Journal of Financial Economics.

Benmelech, Efraim, Ralf R. Meisenzahl, and Rodney Ramcharan, 2016. The Real Effects of Liquidity During the Financial Crisis: Evidence from Automobiles. The Quarterly Journal of Economics 132, 317–365.

Bentolila, Samuel, Marcel Jansen, and Gabriel Jiménez, 2017. When Credit Dries Up: Job Losses in the Great Recession. Journal of the European Economic Association 16, 650–695.

Berger, Allen, Scott Frame, and Vasso Ioannidou, 2011. Tests of Ex Ante versus Ex Post Theories of Collateral Using Private and Public Information. Journal of Financial Economics.

Berger, Allen N., Marco A. Espinosa-Vega, W. Scott Frame, and Nathan H. Miller, 2011. Why do Borrowers Pledge Collateral? New Empirical Evidence on the Role of Asymmetric Information. Journal of Financial Intermediation 20, 55 – 70.

Berger, Allen N., W. Scott Frame, and Vasso Ioannidou, 2016. Reexamining the Empirical Relation Between Loan Risk and Collateral: The Roles of Collateral Liquidity and Types. Journal of Financial Intermediation 26, 28 – 46.

Berger, Allen N., Iftekhar Hasan, and Mingming Zhou, 2010. The Effects of Focus versus Diversification on Bank Performance: Evidence from Chinese Banks. Journal of Banking & Finance 34, 1417 – 1435 Performance Measurement in the Financial Services Sector.

Berger, Allen N., and Gregory F. Udell, 1990. Collateral, Loan Quality and Bank Risk. Journal of Monetary Economics 25, 21 – 42.

——— , 1995. Relationship Lending and Lines of Credit in Small Firm Finance. The Journal of Business 68, 351–381.

Berger, Philip G., Michael Minnis, and Andrew Sutherland, 2017. Commercial Lending Concentration and Bank Expertise: Evidence from Borrower Financial Statements. Journal of Accounting and Economics 64, 253 – 277.

Bernanke, Ben S, 1983. Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression. The American Economic Review 73, 257–276.

Besanko, David, and Anjan V. Thakor, 1987a. Collateral and Rationing: Sorting Equilibria in Monopolistic and Competitive Credit Markets. International Economic Review 28, 671–689.

——— , 1987b. Competitive Equilibrium in the Credit Market Under Asymmetric Information.. Journal of Economic Theory 42, 167–182.

Bester, Helmut, 1985. Screening vs. Rationing in Credit Markets with Imperfect Information. The American Economic Review 75, 850–855.

——— , 1987. The Role of Collateral in Credit Markets with Imperfect Information. European Economic Review 31, 887 – 899 Special Issue on Market Competition, Conflict and Collusion.

Boot, Arnoud W. A., and Anjan V. Thakor, 1994. Moral Hazard and Secured Lending in an Infinitely Repeated Credit Market Game. International Economic Review 35, 899–920.

——— , 2000. Can Relationship Banking Survive Competition?. The Journal of Finance 55, 679–713.

——— , and Gregory F. Udell, 1991. Secured Lending and Default Risk: Equilibrium Analysis, Policy Implications and Empirical Results. The Economic Journal 101, 458–472.

Bord, Vitaly, Victoria Ivashina, and Ryan Taliaferro, 2018. Large Banks and Small Firm Lending. Working Paper.

Boyd, John H, and Edward C Prescott, 1986. Financial Intermediary-Coalitions. Journal of Economic Theory 38, 211 – 232.

Brick, Ivan E., and Darius Palia, 2007. Evidence of Jointness in the Terms of Relationship Lending. Journal of Financial Intermediation 16, 452 – 476.

Caballero, Ricardo J., Takeo Hoshi, and Anil K. Kashyap, 2008. Zombie Lending and Depressed Restructuring in Japan. American Economic Review 98, 1943–77.

Calomiris, Charles, Mauricio Larrain, José Liberti, and Jason Sturgess, 2017. How Collateral Laws Shape Lending and Sectoral Activity. Journal of Financial Economics.

Campello, Murillo, and Erasmo Giambona, 2013. Real Assets and Capital Structure. The Journal of Financial and Quantitative Analysis 48, 1333–1370.

Campello, Murillo, and Mauricio Larrain, 2015. Enlarging the Contracting Space: Collateral Menus, Access to Credit, and Economic Activity. The Review of Financial Studies 29, 349–383.

Carey, Mark, Mitch Post, and Steven A. Sharpe, 1998. Does Corporate Lending by Banks and Finance Companies Differ? Evidence on Specialization in Private Debt Contracting. The Journal of Finance 53, 845–878.

Cerqueiro, Geraldo, Steven Ongena, and Kasper Roszbach, 2016. Collateralization, Bank Loan Rates, and Monitoring. The Journal of Finance 71, 1295–1322.

——— , 2019. Collateral Damaged? Priority Structure, Credit Supply, and Firm Performance. Journal of Financial Intermediation p. 100824.

Chakraborty, Atreya, and Charles X. Hu, 2006. Lending Relationships in Line-of-Credit and Nonline-of-Credit Loans: Evidence from Collateral use in Small Business. Journal of Financial Intermediation 15, 86 – 107.

Chan, Yuk-Shee, and Anjan V. Thakor, 1987. Collateral and Competitive Equilibria with Moral Hazard and Private Information. The Journal of Finance 42, 345–363.

Chaney, Thomas, David Sraer, and David Thesmar, 2012. The Collateral Channel: How Real Estate Shocks Affect Corporate Investment. American Economic Review 102, 2381–2409.

Chen, Brian, Samuel Hanson, and Jeremy Stein, 2017. The Decline of Big-Bank Lending to Small Business: Dynamic Impacts on Local Credit and Labor Markets. Working Paper.

Chodorow-Reich, Gabriel, 2013. The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-9 Financial Crisis. The Quarterly Journal of Economics 129, 1–59.

Cole, Rebel A., Lawrence G. Goldberg, and Lawrence J. White, 2004. Cookie Cutter vs. Character: The Micro Structure of Small Business Lending by Large and Small Banks. The Journal of Financial and Quantitative Analysis 39, 227–251.

Cooley, Thomas, Ramon Marimon, and Vincenzo Quadrini, 2004. Aggregate Consequences of Limited Contract Enforceability. Journal of Political Economy 112, 817–847.

Cortés, Kristle, Yuliya Demyanyk, Lei Li, Elena Loutskina, and Philip Strahan, 2018. Stress Tests and Small Business Lending. NBER Working Paper Series.

Covas, Francisco, 2018. Capital Requirements in Supervisory Stress Tests and Their Adverse Impact on Small Business Lending. TCH Working Paper.

Degryse, Hans, and Steven Ongena, 2004. The Impact of Competition on Bank Orientation and Specialization. CEPR Discussion Papers 4543.

Dell'Ariccia, Giovanni, Ezra Friedman, and Robert Marquez, 1999. Adverse Selection as a Barrier to Entry in the Banking Industry. The RAND Journal of Economics 30, 515–534.

Dell'Ariccia, Giovanni, and Robert Marquez, 2004. Information and Bank Credit Allocation. Journal of Financial Economics 72, 185 – 214.

DeYoung, R., A. Gron, G. Torna, and A. Winton, 2015. Risk Overhang and Loan Portfolio Decisions: Small Business Loan Supply before and during the Financial Crisis. The Journal of Finance 70, 2451–2488.

Diamond, Douglas W, 1984. Financial Intermediation and Delegated Monitoring. The Review of Economic Studies 51, 393–414.

Diamond, Douglas W., Yunzhi Hu, and Raghuram G. Rajan, 2019. Pledgeability, Industry Liquidity, and Financing Cycles. Journal of Finance.

Donaldson, Jason Roderick, Denis Gromb, and Giorgia Piacentino, 2019. The Paradox of Pledgeability. Journal of Financial Economics.

Drechsel, Thomas, 2019. Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations. Working Paper.

Edgerton, Jesse, 2012. Credit Supply and Business Investment During the Great Recession: Evidence from Public Records of Equipment Financing. Working Paper.

Eisfeldt, Andrea L., and Adriano A. Rampini, 2008. Leasing, Ability to Repossess, and Debt Capacity. The Review of Financial Studies 22, 1621–1657.

Fricke, Daniel, and Tarik Roukny, 2018. Generalists and Specialists in the Credit Market. Journal of Banking & Finance p. 105335.

Gale, Douglas, and Martin Hellwig, 1985. Incentive-Compatible Debt Contracts: The One-Period Problem. The Review of Economic Studies 52, 647–663.

Gan, Jie, 2007. The Real Effects of Asset Market Bubbles: Loan- and Firm-Level Evidence of a Lending Channel. The Review of Financial Studies 20, 1941–1973.

Giambona, Erasmo, Antonio S. Mello, and Timothy J. Riddiough, 2018. Real Assets, Collateral and the Limits of Debt Capacity. Real Estate Economics 46, 836–886.

Granja, João, Christian Leuz, and Raghuram Rajan, 2018. Going the Extra Mile: Distant Lending and Credit Cycles. Working Paper 25196 National Bureau of Economic Research.

Greenstone, M, A Mas, and H.-L Nguyen, 2014. Do Credit Market Shocks Affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and 'Normal' Economic Times. Working Paper.

Hauswald, Robert, and Robert Marquez, 2006. Competition and Strategic Information Acquisition in Credit Markets. The Review of Financial Studies 19, 967–1000.

Hoberg, Gerard, and Gordon Phillips, 2010. Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis. The Review of Financial Studies 23, 3773–3811.

——— , 2016. Text-Based Network Industries and Endogenous Product Differentiation. Journal of Political Economy 124, 1423–1465.

Holmstrom, Bengt, and Jean Tirole, 1997. Financial Intermediation, Loanable Funds, and the Real Sector. The Quarterly Journal of Economics 112, 663–691.

Hubbard, R. Glenn, Kenneth N. Kuttner, and Darius N. Palia, 2002. Are There Bank Effects in Borrowers' Costs of Funds? Evidence from a Matched Sample of Borrowers and Banks. The Journal of Business 75, 559–581.

Ivashina, V., L. Laeven, and E. Moral-Benito, 2019. Loan Types and the Bank Lending Channel. Working Paper.

Ivashina, Victoria, and David Scharfstein, 2010. Bank Lending During the Financial Crisis of 2008. Journal of Financial Economics 97, 319–338.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, 2017. Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments. Journal of Political Economy 125, 2126–2177.

Jiménez, Gabriel, Vicente Salas, and Jesús Saurina, 2006. Determinants of Collateral. Journal of Financial Economics 81, 255 – 281.

Jiménez, Gabriel, and Jesús Saurina, 2004. Collateral, Type of Lender and Relationship Banking as Determinants of Credit Risk. Journal of Banking & Finance 28, 2191 – 2212.

John, Kose, Anthony W. Lynch, and Manju Puri, 2003. Credit Ratings, Collateral, and Loan Characteristics: Implications for Yield. The Journal of Business 76, 371–409.

Kelly, Bryan T., Dimitris Papanikolaou, Amit Seru, and Matt Taddy, 2018. Measuring Technological Innovation over the Long Run. Yale ICF Working Paper.

Khwaja, Asim Ijaz, and Atif Mian, 2008. Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market. American Economic Review 98, 1413–42.

Laeven, Luc, and Ross Levine, 2007. Is there a Diversification Discount in Financial Conglomerates?. Journal of Financial Economics 85, 331 – 367 The economics of conflicts of interest financial institutions.

Leeth, John D., and Jonathan A. Scott, 1989. The Incidence of Secured Debt: Evidence from the Small Business Community. The Journal of Financial and Quantitative Analysis 24, 379–394.

Lian, Chen, and Yueran Ma, 2019. Anatomy of Corporate Borrowing Constraints. Working Paper.

Liberti, José, Jason Sturgess, and Andrew Sutherland, 2017. Information Sharing and Lender Specialization: Evidence from the U.S. Commercial Lending Market. Working Paper.

Liberti, Jose Maria, and Jason Sturgess, 2014. Uncovering Collateral Constraints. Working Paper.

Loutskina, Elena, and Philip E. Strahan, 2011. Informed and Uninformed Investment in Housing: The Downside of Diversification. The Review of Financial Studies 24, 1447–1480.

Mello, António S., and Martin Ruckes, 2017. Collateral in Corporate Financing. in Working Paper.

Mian, Atif, and Amir Sufi, 2009. The Consequences of Mortgage Credit Expansion: Evidence from the US Mortgage Default Crisis. The Quarterly Journal of Economics 124, 1449–1496.

——— , 2018. Credit Supply and Housing Speculation. Working Paper.

Murfin, Justin, and Ryan Pratt, 2019. Who Finances Durable Goods and Why It Matters: Captive Finance and the Coase Conjecture. The Journal of Finance 74, 755–793.

Ortiz-Molina, Hernán, and Gordon M. Phillips, 2014. Real Asset Illiquidity and the Cost of Capital. Journal of Financial and Quantitative Analysis 49, 1–32.

Paravisini, Daniel, Veronica Rappoport, and Philipp Schnabl, 2018. Specialization in Bank Lending: Evidence from Exporting Firms. NBER Working Paper.

Peek, Joe, and Eric S. Rosengren, 2000. Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States. American Economic Review 90, 30–45.

Petersen, Mitchell A., and Raghuram G. Rajan, 1994. The Benefits of Lending Relationships: Evidence from Small Business Data. The Journal of Finance 49, 3–37.

——— , 1995. The Effect of Credit Market Competition on Lending Relationships. The Quarterly Journal of Economics 110, 407–443.

——— , 2002. Does Distance Still Matter? The Information Revolution in Small Business Lending. The Journal of Finance 57, 2533–2570.

Pulvino, Todd C., 1998. Do Asset Fire Sales Exist? An Empirical Investigation of Commercial Aircraft Transactions. The Journal of Finance 53, 939–978.

Rajan, Raghuram, Henri Servaes, and Luigi Zingales, 2000. The Cost of Diversity: The Diversification Discount and Inefficient Investment. The Journal of Finance 55, 35–80.

Rajan, Raghuram, and Andrew Winton, 1995. Covenants and Collateral as Incentives to Monitor. The Journal of Finance 50, 1113–1146.

Rajan, Raghuram G., 1992. Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt. The Journal of Finance 47, 1367–1400.

Schlingemann, Frederik P., René M. Stulz, and Ralph A. Walkling, 2002. Divestitures and the Liquidity of the Market for Corporate Assets. Journal of Financial Economics 64, 117 – 144.

Schnabl, Philipp, 2012. The International Transmission of Bank Liquidity Shocks: Evidence from an Emerging Market. The Journal of Finance 67, 897–932.

Schwert, Michael, 2018. Bank Capital and Lending Relationships. The Journal of Finance 73, 787–830.

Shleifer, Andrei, and Robert W. Vishny, 1992. Liquidation Values and Debt Capacity: A Market Equilibrium Approach. Journal of Finance.

——— , 2010. Fire Sales in Finance and Macroeconomics. NBER Working Papers 16642 National Bureau of Economic Research, Inc.

Stein, Jeremy C., 2002. Information Production and Capital Allocation: Decentralized versus Hierarchical Firms. Journal of Finance LVII, 1891–1921.

Stiglitz, Joseph, and Andrew Weiss, 1981. Credit Rationing in Markets with Imperfect Information. The.

Stroebel, Johannes, 2016. Asymmetric Information about Collateral Values. The Journal of Finance 71, 1071–1112.

Townsend, Robert M, 1979. Optimal Contracts and Competitive Markets with Costly State Verification. Journal of Economic Theory 21, 265 – 293.

Vig, Vikrant, 2013. Access to Collateral and Corporate Debt Structure: Evidence from a Natural Experiment. The Journal of Finance 68, 881–928.

Williamson, Stephen D., 1986. Costly Monitoring, Financial Intermediation, and Equilibrium Credit Rationing. Journal of Monetary Economics 18, 159 – 179.

Winton, Andrew, 1999. Don't Put All Your Eggs in One Basket? Diversification and Specialization in Lending. Manuscript, University of Minnesota.

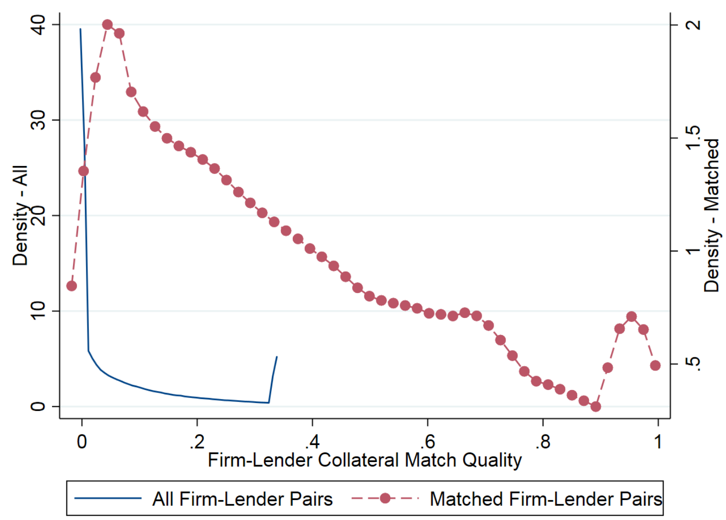
6 Figures

Figure 1: Firm-Lender Collateral Match

This figure plots the kernel density for Firm-Lender Collateral Match Quality. Values are capped at 5th and 95th percentiles.

(a) **Firm-Lender Pre-Crisis Collateral Match**

The solid line includes all potential firm-lender pairs based on the total set of borrowers and lenders in the sample. The dashed line plots the firm-lender collateral match scores for equilibrium observed firm-lender matches with at least one loan between the pair in the pre-crisis (2002-07) period.



(b) **Firm-Lender Collateral Match - Pre-Crisis vs. Post-Crisis**

The solid line includes all firm-lender pairs with at least one loan between the borrower and lender in the pre-crisis (2002-07) period. The dashed line includes all firm-lender pairs with at least one loan between the borrower and lender in both the pre-crisis (2002-07) and post (2008-16) period

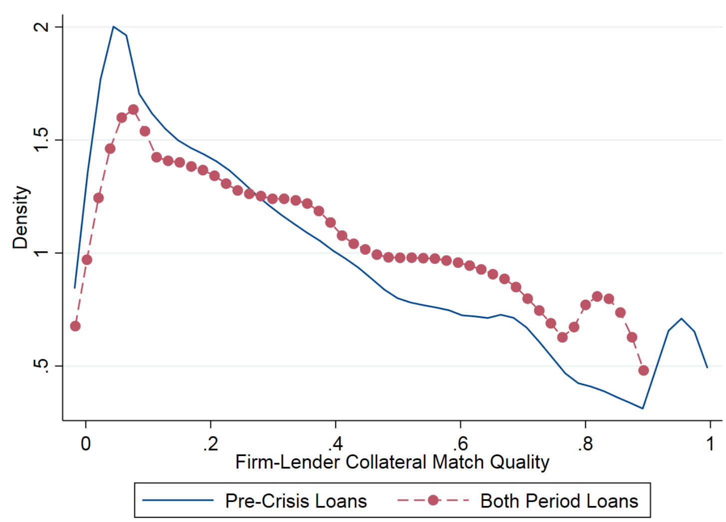


Figure 2: Firm-Lender Collateral Match Quality

This figure plots lending to firm-lender pairs with a lending relationship between 2002-07. Firm-Lender Collateral Match Quality is measured based on comparison of firm's collateral to lending portfolio of the lender based on pre-crisis loans (2002-07). Pairs are classified into above and below median collateral match quality. Lending across the two groups is plotted between 2002-16.

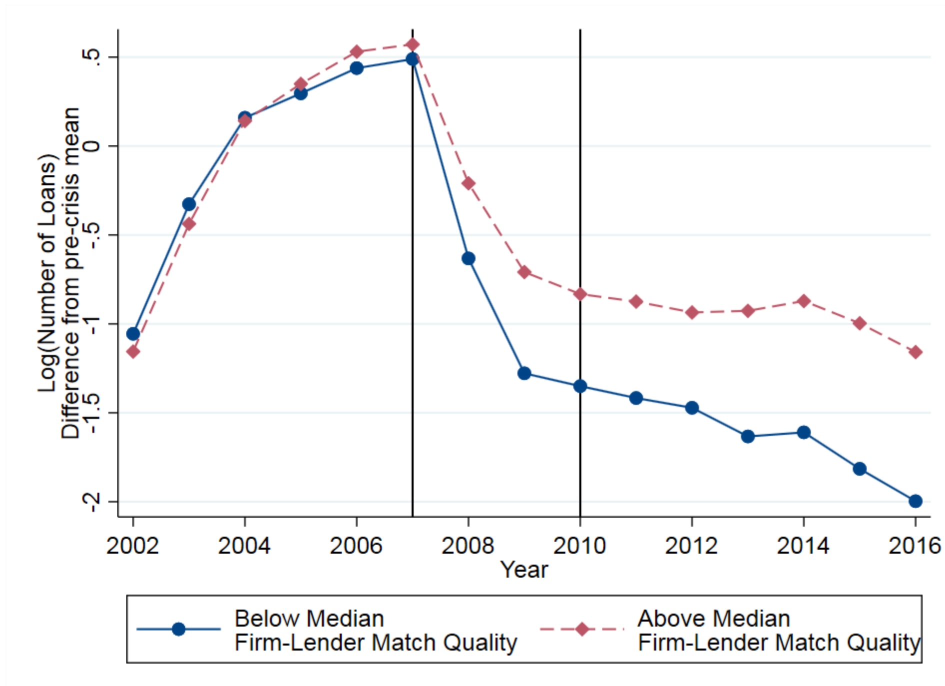
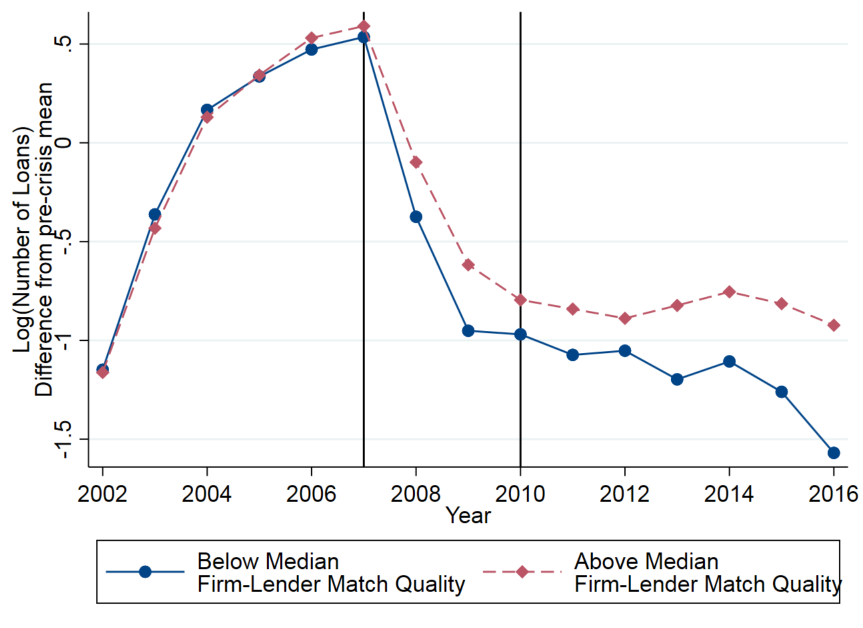


Figure 3: Firm-Lender Collateral Match Quality - Within Group

Firm-Lender Collateral Match Quality is measured based on comparison of firm's collateral to lending portfolio of the lender based on pre-crisis loans (2002-07).

(a) **Within Firm**

Within each firm, lenders with pre-crisis relationship are classified into above and below median collateral match quality. Sample restricted to firms with multiple lending relationships. Lending across the two groups is plotted between 2002-16.



(b) **Within Lender**

Within each lender, firms that borrowed at least once between 2002-07 are categorized as having high vs. low colllateral match. Lending across the two groups is plotted between 2002-16

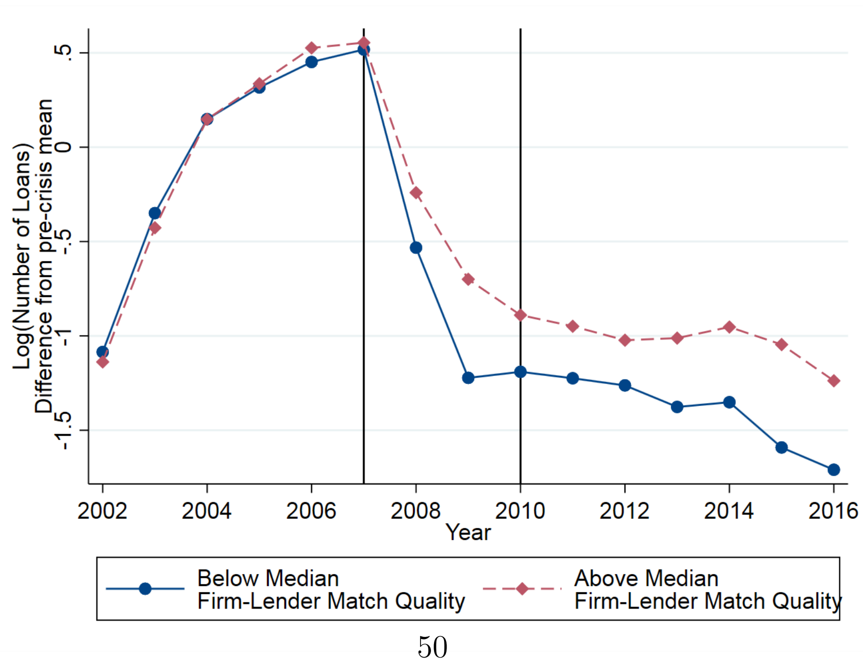


Figure 4: Firm-Lender Collateral Match Quality - New Matches

This figure plots the kernel density for firm-lender collateral match scores. The solid line includes all potential firm-lender pairs based on the total set of borrowers and lenders in the sample. The dashed line plots the distribution of scores for firm-lender pairs with a match in the post-crisis (2008-16) period. Match score is calcualted based on pre-crisis (2002-07) collateral portfolio of the borrower and lender.

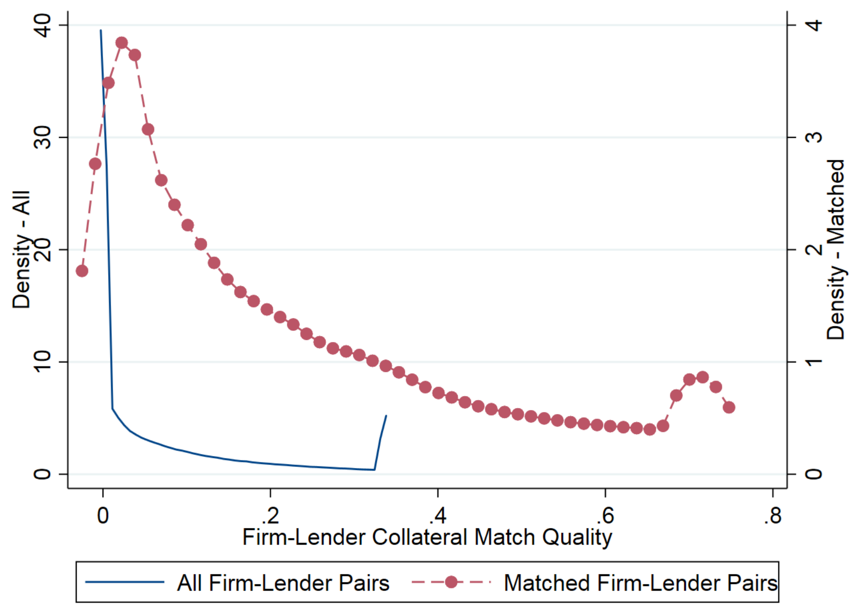
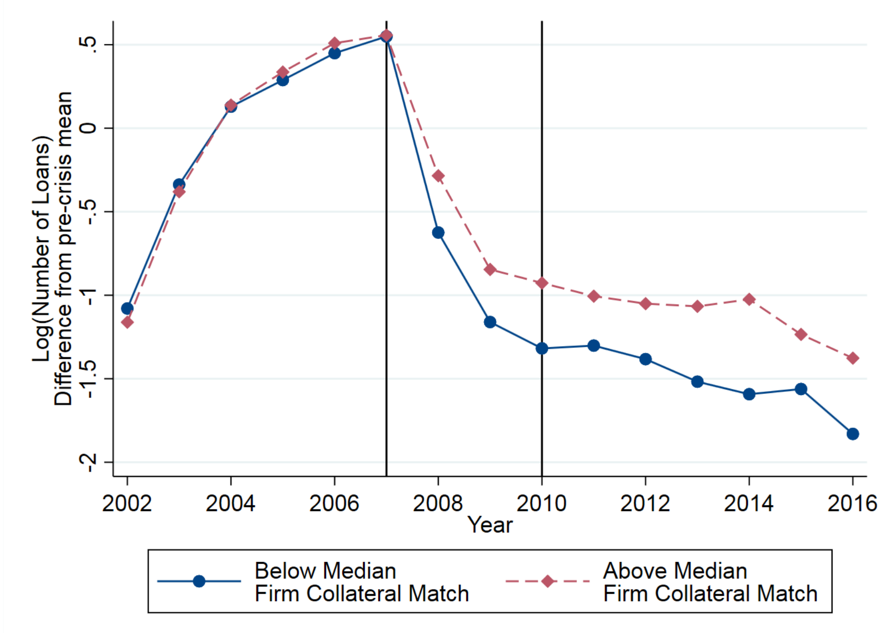


Figure 5: Firm-Level Lending

Sample includes firms in Texas with at least one loan in the pre-crisis (2002-07) period.

(a) **Firm Collateral Match Quality - Relationship Lending**

Firm-level collateral match quality is created using a weighted average of firm-lender level collateral matches. Lending to firms from lenders with pre-crisis (2002-07) relationship is plotted.



(b) **Firm Similarity - Total Lending**

Firm Similarity is a measure of collateral match between the borrower and (weighted) average of all lenders in the sample based on pre-crisis (2002-07) collateral of borrower and lender. Total annual lending to the firm is plotted.

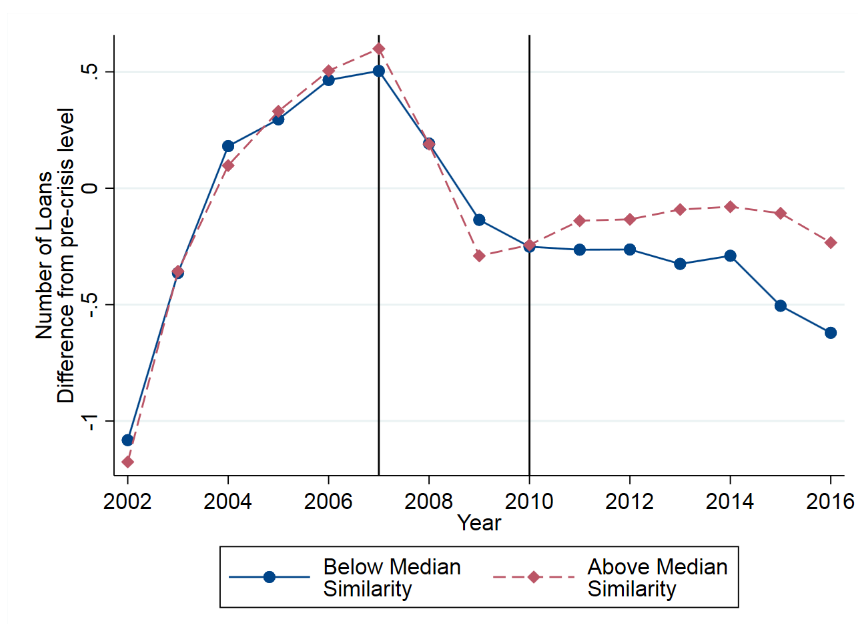
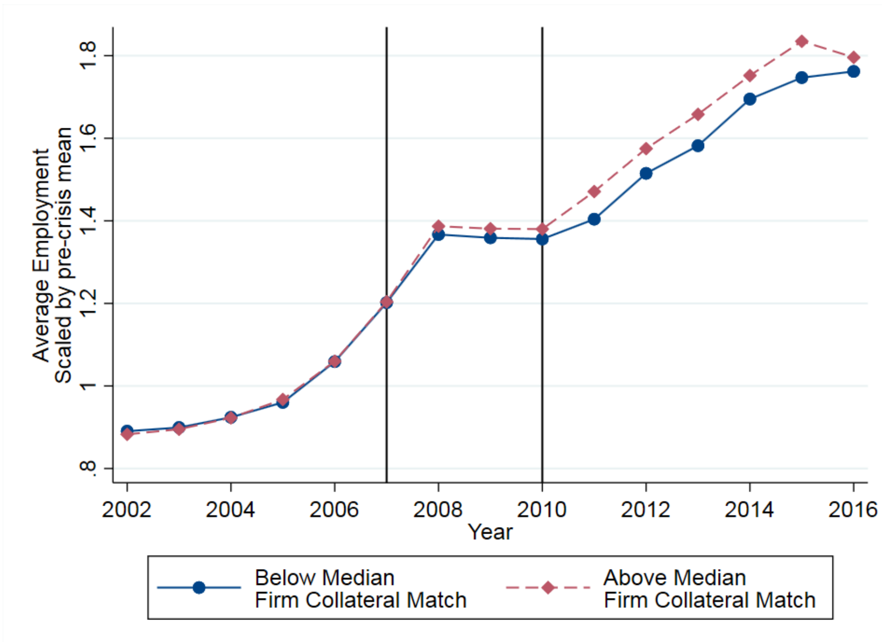


Figure 6: Firm Employment

Firm-level collateral match quality is created using a weighted average of firm-lender level collateral matches. Firm Similarity is a measure of collateral match between the borrower and (weighted) average of all lenders in the sample. Average of scaled firm-level employment is plotted. Employment is scaled by the average employment at the firm in the pre-crisis period (2002-07).

(a) **Firm Collateral Match**



(b) **Firm Similarity**

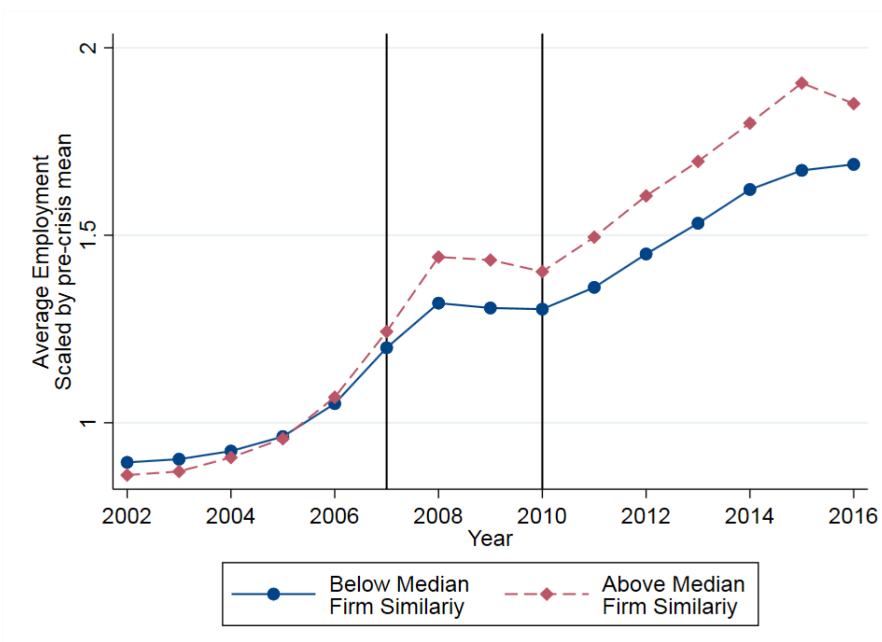


Figure 7: Regression Betas

Coefficients from the following regression specification are plotted -

$$\text{Scaled Employment}_{ft} = \alpha + \text{Firm Similarity}_f \times \mathbf{1}_t + \delta_t + \epsilon_{ft}$$

for firm f, in year t where Scaled Employment is annual firm employment scaled by average pre-crisis level of employment at the firm. Firm Similarity is a measure of collateral match between the borrower and (weighted) average of all lenders in the sample based on pre-crisis (2002-07) collateral plegded by firms. $\mathbf{1}_t$ takes value 1 in year t and is zero otherwise. Regression includes time fixed effects (δ_t). Regression is weighted by the firm employment in 2007.

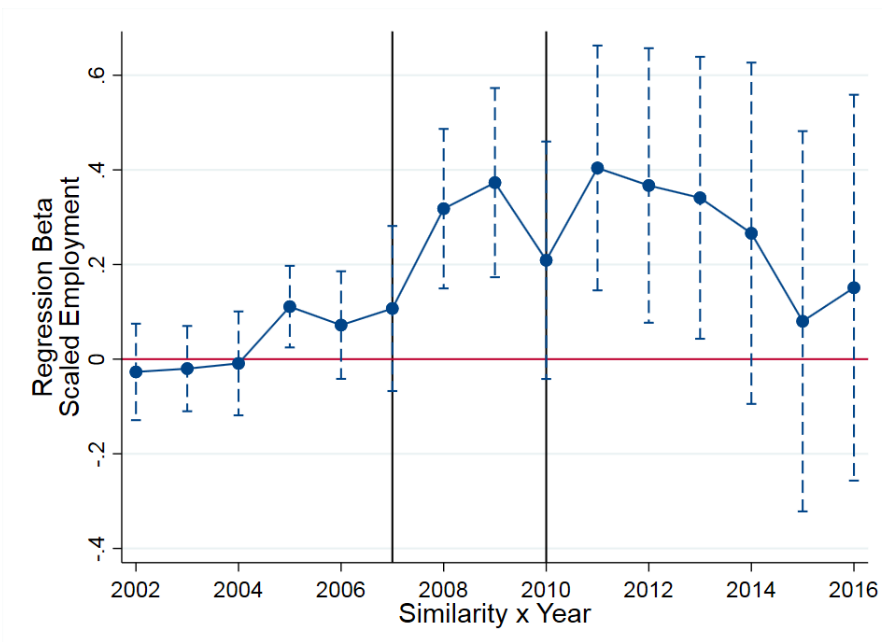
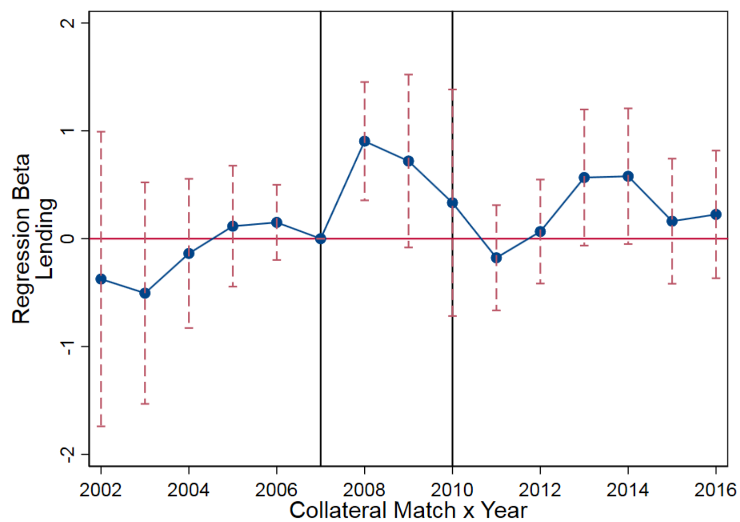


Figure 8: Zombie Lending

Coefficients from the following regression specification are plotted -

$$\begin{aligned} \mathbf{y}_{flt} =& \alpha_{fl} + \delta_t + \beta_{1t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \\ & \beta_{2t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t \times \text{Low Capital}_l + \epsilon_{fci} \end{aligned}$$

for firm f, lender l and year t. Dependent variable is an indicator for whether a firm gets a loan in a given year scaled by number of times the firm got a loan in the pre-crisis (2002-07) period. Firm-lender Collateral Match is measured based on a comparison of the firm's real assets to the lender's collateral portfolio based on pre-crisis (2002-07) loans. Low capital takes value 1 for lenders with below median Tier 1 capital ratio as of December 2006. Regression includes firm-lender (α_{fl}) and time (δ_t) fixed effects. $\mathbf{1}_t$ takes value 1 in year t and is zero otherwise. Sample is restricted to loans made by banks (commercial bank, nonbank-subsidiary of bank holding company, or a credit union). The figures below plot the time varying coefficients on β_{1t} and β_{2t} respectively.



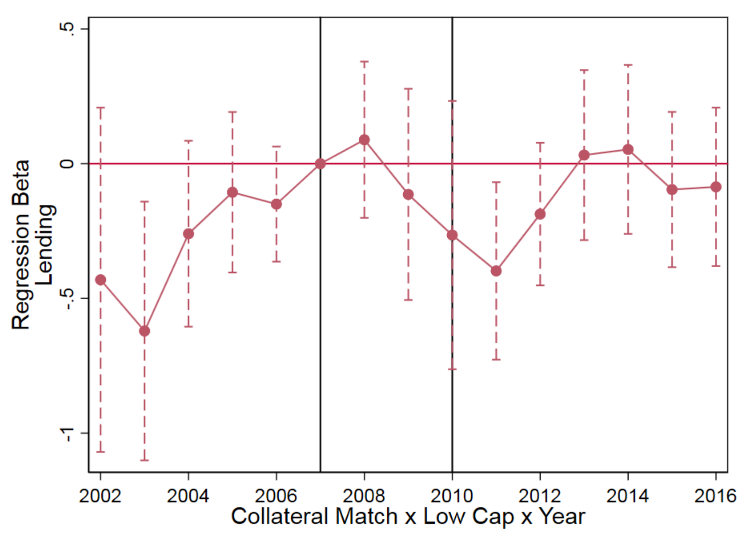
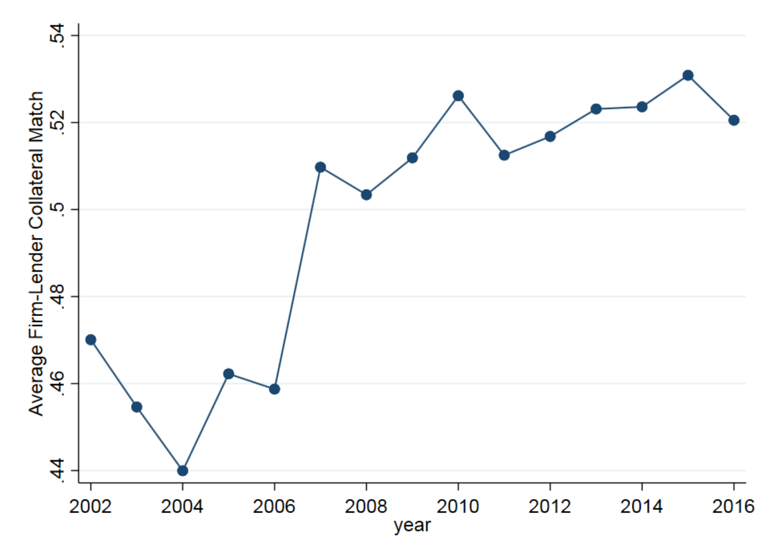


Figure 9: Aggregate Trends

Firm-lender collateral match quality is calculated based on all loans in the sample between 2002 and 2016.

(a) **Average Firm-Lender Collateral Match Quality**

This figure plots the average level of Firm-Lender Collateral Match Quality over time for firm-lender pairs with a loan in the given year.

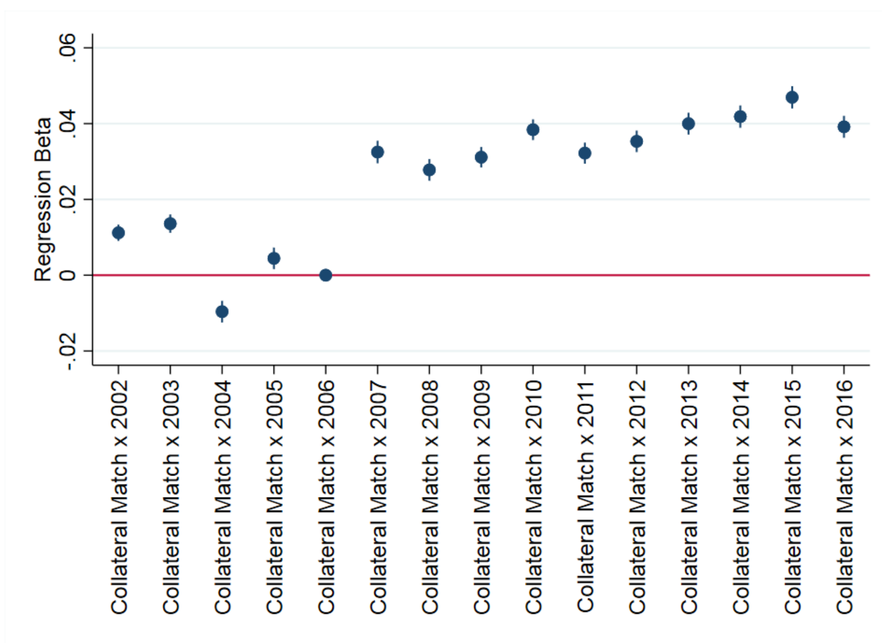


(b) **Dynamic Difference-in-Difference**

This figure plots the coefficeints from the following regression:

$$\mathbf{1}_{flt} = \alpha_f + \gamma_l + \delta_t + \beta \text{Firm-Lender Collateral Match}_{fl} + \epsilon_{flt}$$

$\mathbf{1}_{flt}$ takes value of one if the firm f gets a loan from lender l in year t. The sample includes all firm-lender pairs with at least one loan between 2002-16.



7 Tables

Table 1: Summary Statistics

Panel A - Independent Variables

Firm-lender sample includes firm-lender pairs with at least one loan in the pre-crisis (2002-07). Firm sample includes firms with at least one loan in the pre-crisis period. At the firm-lender level, repeat loan takes value 1 if the firm gets a loan in 2008-16 from the same lender. At the firm level, repeat loan takes a value of one if firm gets a repeat loan from any of its relationship lenders in the post-crisis period. New Loan takes value 1 if firm gets any loan in the post-crisis period, irrespective of whether the firm and lender had a pre-crisis relationship. New Lender takes value 1 if the firm gets at least one loan from a lender it did not borrow from in the pre-crisis period. Scaled Loan is dummy for whether a loan is observed for the firm-lender pair in a given year scaled by the average number of pre-crisis loans between the borrower-lender pair. Average employment change is the second-order approximation of log difference in firm employment between the pre-crisis and post-crisis periods, bounded between [-2,2]. Scaled Employment is annual firm employment scaled by pre-crisis level of firm employment.

	Mean	SD	N
Repeat Loan (Firm-Lender Level)	0.1976	0.3982	38500
Repeat Loan - Multi-relationship firms (Firm-Lender Level)	0.2074	0.4055	23000
Repeat Loan (Firm-Level)	0.3083	0.4618	23500
New Loan - Total (Firm-Level)	0.6158	0.4864	23500
New Lender (Firm-Level)	0.5244	0.4994	23500
Scaled Loan (Firm-Lender-Year Level)	0.5839	1.647	514000
Average Employment Change (2002-07 to 2008-16) (Firm-Level)	0.06643	0.6502	23500
Average Scaled Employment (Firm-Year Level)	1.098	0.8322	303000

Panel B - Firm-Lender Collateral Match Quality

Firm-Lender Collateral Match Quality is measured based on comparison of firm's collateral to lending portfolio of the lender based on pre-crisis loans (2002-07). Firm Collateral Match is the firm-level weighted average of firm-lender collateral match quality. Firm Similarity is measured based on comaprison of firm's real assets in the pre-crisis period to the (weighted) average lender.

	Firm-Lender Collateral Match Quality	Firm Collateral Match	Firm Similarity
Mean	0.3827	0.3822	0.2182
Standard Deviation	0.3085	0.285	0.1531
Pseudo 10th pct (mean of 9 - 11)	0.01649	0.02959	0.03513
Pseudo 25th pct (mean of 24 - 26)	0.09444	0.137	0.08723
Pseudo 75th pct (mean of 74 - 76)	0.6054	0.5727	0.3184
Pseudo 90th pct (mean of 89 - 91)	0.8619	0.8083	0.4323

Table 1: Summary Statistics - Contd.

Panel C - Dependent Variables

Firm Age is the log of the number of years the firm has been in operation as of 2007. Firm Size is the log of employment at the firm in 2007. Industry shares at the 2,3,6 digit are calculated as the pre-crisis (2002-07) share of the industry in the lender's portfolio. Lender share is the share of lending from the lender in the borrower's portolfio. Avg. number of past loans is the average annual number of loans between the borrower and lender in the pre-crisis period. Time from last loan is the number of years since the last loan between the borrower-lender pair and 2007. Bank takes value of one if the lender is a commercial bank, nonbank subsidiary of bank holding company, or a credit union. Top 4 takes value of 1 if the lender is one of the large four commercial banks - JPMorgan Chase, Wells Fargo, Bank of America, or Citibank. Captive takes value one if the lender is a captive finance company, i.e., financing arm of a manufacturing company. Industry performance at 3,4,6-digit NAICS level is measured as the weighted average change in employment at firms in the industry over a three year window around the financial crisis (average 2008-10 level change from 2005-07 level).

	Mean	SD
Firm Age (2007)	12.73	9.901
Firm Size (2007)	2.648	1.513
2-digit Industry Share	0.2448	0.2663
4-digit Industry Share	0.09348	0.172
6-digit Industry Share	0.07705	0.1592
Lender Share	0.3391	0.2007
Avg. Number of past loans	0.3764	0.4248
Time from last loan	1.531	1.457
Bank	0.4402	0.4964
Top4	0.1209	0.3261
Captive	0.1738	0.3789
3-digit NAICS performance	-0.2985	0.1031
4-digit NAICS performance	-0.3066	0.1344
6-digit NAICS performance	-0.3152	0.1739

Table 2: Within-Firm Regression

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firm-lender pairs with a loan between 2002 and 2007. Dependent variable takes a value of 1 if the firm gets a new loan after 2008 from the same lender. Firm-Lender Collateral Match is measured based on real assets pledged by the firm between 2002 and 2007, compared to the collateral accepted by the lender. Measure is at the firm-lender level.

$$\text{Repeat Loan}_{fl} = \alpha_f + \gamma_l + \beta_{\mathbf{1}}\text{Firm-Lender Collateral Match Quality}_{fl} + \epsilon_{fl}$$

Firm controls include the firm size measured by employment, and firm age in 2007.
Columns 1-3 include the full sample of firms. Columns 4-6 are restricted to firms with multiple relationships.

	All Firms				Multi-Relationship Firms		
	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan	(6) Loan	(7) Loan
Firm-Lender Collateral Match Quality	0.066*	0.078**	0.083**	0.082***	0.109***	0.106***	0.120***
	(0.034)	(0.031)	(0.032)	(0.029)	(0.021)	(0.040)	(0.022)
Observations	38500	38500	38500	38500	23000	23000	23000
County x Industry FE	N	Y	N	Y	Y	N	N
Lender FE	N	N	Y	Y	Y	N	Y
Firm Controls	N	N	N	Y	Y	N	N
Firm FE	N	N	N	N	N	Y	Y
R^2	0.003	0.077	0.158	0.215	0.265	0.388	0.528

Table 3: Firm-Lender Lending - Dynamic Diff-in-diff

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firm-lender pairs with a loan between 2002 and 2007. Dependent variable is an indicator that takes value one if a loan is observed for a firm-lender pair in a given year

$$\mathbf{y}_{flt} = \alpha_f + \gamma_l + \delta_t + \beta_t \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \epsilon_{fci}$$

where firm f, lender l, and year t. The dependent variable is an indicator that takes value of one if the firm-lender pair is observed to have a loan in a given year, scaled by frequency of loans between the pair in the pre-crisis period. I scale the loans for a measure of percentage change in lending

	(1)	(2)	(3)	(4)
	Loan	Loan	Loan	Loan
Firm-Lender Similarity x 2002	-0.108	-0.120***	0.146	-0.028
	(0.076)	(0.037)	(0.119)	(0.041)
Firm-Lender Similarity x 2003	-0.119**	-0.013	0.136	-0.216***
	(0.057)	(0.045)	(0.103)	(0.067)
Firm-Lender Similarity x 2004	-0.136***	-0.099*	0.119	-0.162**
	(0.049)	(0.057)	(0.083)	(0.065)
Firm-Lender Similarity x 2005	-0.080	0.015	0.176**	-0.070
	(0.051)	(0.051)	(0.075)	(0.064)
Firm-Lender Similarity x 2006	0.026	0.012	0.279***	0.117*
	(0.063)	(0.052)	(0.065)	(0.067)
Firm-Lender Similarity x 2007	-0.254***	-0.243***		0.01
	(0.067)	(0.061)	0	(0.072)
Firm-Lender Similarity x 2008	0.350***	0.298***	0.604***	0.223***
	(0.051)	(0.047)	(0.081)	(0.064)

Continued on next page

Table 3 – *Continued from previous page*

	(1)	(2)	(3)	(4)
	Loan	Loan	Loan	Loan
Firm-Lender Similarity x 2009	0.306***	0.311***	0.560***	0.152***
	(0.062)	(0.044)	(0.103)	(0.051)
Firm-Lender Similarity x 2010	0.227***	0.203***	0.481***	0.084
	(0.064)	(0.044)	(0.111)	(0.054)
Firm-Lender Similarity x 2011	0.082	0.089**	0.335***	0.113**
	(0.055)	(0.045)	(0.077)	(0.053)
Firm-Lender Similarity x 2012	0.077*	0.051	0.328***	0.117***
	(0.045)	(0.046)	(0.062)	(0.045)
Firm-Lender Similarity x 2013	0.135***	0.102**	0.386***	0.151***
	(0.041)	(0.044)	(0.072)	(0.049)
Firm-Lender Similarity x 2014	0.152***	0.137***	0.403***	0.152***
	(0.039)	(0.044)	(0.071)	(0.042)
Firm-Lender Similarity x 2015	0.077**	0.019	0.327***	0.097**
	(0.034)	(0.034)	(0.068)	(0.049)
Firm-Lender Similarity x 2016	0.051	0.029	0.300***	0.054
	(0.035)	(0.037)	(0.069)	(0.055)
Observations	514000	514000	514000	308000
Firm FE	Y	Y	N	N
Lender FE	Y	N	N	N
Year FE	Y	N	Y	Y
Lender x Year FE	N	Y	N	N
Firm x Lender FE	N	N	Y	Y
R^2	0.173	0.276	0.192	0.496

Table 4: Industry vs. Collateral Specialization

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firm-lender pairs with a loan between 2002 and 2007. Dependent variable takes a value of 1 if the firm gets a new loan after 2008 from the same lender. Firm-lender Collateral Match is measured based on a comparison of the firm's real assets to the lender's collateral portfolio.

Panel A - Inclusion of Lender-Industry fixed effects

	(1) Loan	(2) Loan	(3) Loan
Firm-Lender Collateral Match Quality	0.120***	0.132***	0.134***
	(0.022)	(0.026)	(0.027)
Observations	23000	23000	23000
Firm FE	Y	Y	Y
Lender FE	Y	N	N
Lender x 2-digit NAICS FE	N	Y	N
Lender x 3-digit NAICS FE	N	N	Y
R^2	0.528	0.643	0.703

Panel B - Inclusion of Lender-Industry Shares

	(1) Loan	(2) Loan	(3) Loan
Firm-Lender Collateral Match Quality	0.115***	0.114***	0.114***
	(0.022)	(0.022)	(0.022)
2-digit Industry Share	0.118***		
	(0.029)		
4-digit Industry Share		0.217***	
		(0.047)	
6-digit Industry Share			0.233***
			(0.045)
Observations	23000	23000	23000
Firm FE	Y	Y	Y
Lender FE	Y	Y	Y
R^2	0.529	0.529	0.529

Table 5: Soft vs. Hard Information

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firm-lender pairs with a loan between 2002 and 2007. Dependent variable takes a value of 1 if the firm gets a new loan after 2008 from the same lender. Firm-lender Collateral Match is measured based on a comparison of the firm's real assets to the lender's collateral portfolio.
Controls include the average annual number of pre-crisis loans between the borrower and lender, the lender's share in total lending to the borrower in the pre-crisis period, the number of years between 2007 and the last loan between the borrower and lender.

	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan
Firm-Lender Collateral	0.120***	0.074***	0.068***	0.100***	0.068***
Match Quality	(0.022)	(0.018)	(0.018)	(0.020)	(0.017)
Lender Share		0.405***			0.323***
		(0.028)			(0.027)
Avg. Number of past loans			0.186***		
			(0.011)		
Time From Last Loan				-0.052***	-0.041***
				(0.004)	(0.004)
Observations	23000	23000	23000	23000	23000
Firm FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
R^2	0.528	0.542	0.544	0.541	0.549

Table 6: Lender Heterogeneity

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firm-lender pairs with a loan between 2002 and 2007. Dependent variable takes a value of 1 if the firm gets a new loan after 2008 from the same lender. Firm-lender Collateral Match is measured based on a comparison of the firm's real assets to the lender's collateral portfolio.
Bank is an indicator that takes value 1 if the lender is a commercial bank, nonbank-subsidiary of bank holding company, or a credit union. Top4 is an indicator that takes value 1 for the 4 largest commercial banks by size - JP Morgan Chase, Bank of America, Wells Fargo, or Citibank including acquisitions. Captive finance is an indicator that takes value 1 if the parent company of the lender is a manufacturing company.

	(1) Loan	(2) Loan	(3) Loan
Firm-Lender Collateral Match	0.129***	0.125***	0.091***
	(0.030)	(0.024)	(0.020)
Firm-Lender Collateral Match × Bank	-0.022		
	(0.039)		
Firm-Lender Collateral Match × Captive Finance		0.205***	
		(0.046)	
Firm-Lender Collateral Match × Top4			-0.039
			(0.051)
Observations	23000	23000	23000
Firm FE	Y	Y	Y
Lender FE	Y	Y	Y
R^2	0.528	0.528	0.529

Table 7: Fire Sales Channel

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firm-lender pairs with a loan between 2002 and 2007. Dependent variable takes a value of 1 if the firm gets a new loan after 2008 from the same lender. Firm-lender Collateral Match is measured based on a comparison of the firm's real assets to the lender's collateral portfolio.
Industry performance is measured as the weighted average change in employment at firms in the industry over a three year window around the financial crisis (average 2008-10 level change from 2005-07 level).

	(1) Loan	(2) Loan	(3) Loan
Firm-Lender Collateral Match	0.101**	0.144***	0.137***
	(0.040)	(0.036)	(0.031)
Firm-Lender Collateral Match ×	-.066		
Industry Performance (3-digit NAICS)	(0.103)		
Firm-Lender Collateral Match ×		0.083	
Industry Performance (4-digit NAICS)		(0.080)	
Firm-Lender Collateral Match ×			.06
Industry Performance (6-digit NAICS)			(0.058)
Observations	23000	23000	23000
Firm FE	Y	Y	Y
Lender FE	Y	Y	Y
R^2	0.528	0.528	0.528

Table 8: Aggregate Effects - Counter-factual Exercise

This table presents the aggregate effect on lending under counterfactual firm-lender matching exercises. Sample is restricted to firm-lender pairs with a loan between 2002-07.
Counter-factual excercise calculates change in lending on adjusting firm-lender collateral match quality from current level to counter-factual levels keeping all else about the firm-lender pair the same. Results presented as percentage increase in lending over current level of lending.
For each firm-lender pair, I take as given the collateral plegded between the pair. Given the collateral, I estimate hypothetical collateral match scores to all lenders in the sample. The highest score is assigned as the value for Best Available Match for Collateral.
Second, I consider improvement in lending under hypothetical scenario where specialized lenders exist for all borrowers. I take the 90th percentile, the 95th percentile, and highest firm-lender collateral match score from the full distribution match scores. Lending to the borrower is estimated under the hypothetical scenario where a specialzied lender for the borrower's collateral exists.

Best Available Match for Collateral	14.76%
90th percentile of Firm-Lender Collateral Match	21.76%
95th percentile of Firm-Lender Collateral Match	31.34%
Maximum of Firm-Lender Collateral Match	42.67%

Table 9: Firm-Level Results

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firms with a loan between 2002 and 2007. Dependent variable takes a value of 1 if the firm gets a new loan after 2008 (columns 1-3), or the average annual lending to the firm between 2008-16 as a fraction of average lending between 2002 and 2007 (columns 3-6). Firm Collateral Match is created as a weighted average of firm-lender collateral match values. Firm-lender collateral match is created by comparing collateral pledged by the firm to the collateral accepted by its relationship lenders based on pre-crisis loans. Regression is at the firm level.

$$y_{fci} = \alpha + \beta_1 \text{Firm-Collateral Match}_f + \beta_3 X_f + \gamma_{ci} + \epsilon_{fci}$$

Firm controls include the firm size measured by employment, and firm age in 2007.

Panel A - Relationship Lending

	All Firms			Multi-Relationship Firms		
	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan	(6) Loan
Firm Collateral Match	0.062***	0.072***	0.055***	0.125***	0.155***	0.112***
	(0.010)	(0.010)	(0.010)	(0.027)	(0.031)	(0.031)
Observations	23500	23500	23500	7700	7700	7700
County x Industry FE	N	Y	Y	N	Y	Y
Firm Controls	N	N	Y	N	N	Y
R^2	0.001	0.119	0.147	0.003	0.212	0.229

Panel B - Total Lending

	All Firms			Multi-Relationship Firms		
	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan	(6) Loan
Firm Collateral Match	0.028**	0.028**	0.006	0.050**	0.051**	0.012
	(0.011)	(0.012)	(0.012)	(0.022)	(0.025)	(0.025)
Observations	23500	23500	23500	7700	7700	7700
County x Industry FE	N	Y	Y	N	Y	Y
Firm Controls	N	N	Y	N	N	Y
R^2	0.001	0.102	0.148	0.001	0.192	0.216

Table 10: Firm-Level Results - Substitution

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firms with a loan between 2002 and 2007. Dependent variable takes a value of 1 if the firm gets a loan after 2008 from a lender with no previous relationship. Firm similarity is a measure of collateral match between the borrower and (weighted) average of all lenders in the sample. Firm similarity captures the overall preference for the borrower's collateral from lenders in the economy. Regression is at the firm level.

Panel A - New Lender

	New Lender					
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Similarity	0.285***	0.295***	0.225***	0.311***	0.326***	0.263***
	(0.021)	(0.022)	(0.022)	(0.022)	(0.023)	(0.023)
Firm Collateral Match				-0.047***	-0.054***	-0.067***
				(0.012)	(0.013)	(0.012)
Observations	23500	23500	23500	23500	23500	23500
County x Industry FE	N	Y	Y	N	Y	Y
Firm Controls	N	N	Y	N	N	Y
R^2	0.008	0.105	0.151	0.008	0.106	0.152

Panel B - Total Lending

	New Loan					
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Collateral Match	0.028**	0.028**	0.006			
	(0.011)	(0.012)	(0.012)			
Firm Similarity				0.374***	0.365***	0.301***
				(0.020)	(0.021)	(0.021)
Observations	23500	23500	23500	23500	23500	23500
County x Industry FE	N	Y	Y	N	Y	Y
Firm Controls	N	N	Y	N	N	Y
R^2	0	0.102	0.148	0.014	0.114	0.156

Table 11: Employment Results - Relationship Lending

This table includes firms in Texas with a loan between 2002-07. Average employment change is the second-order approximation of log difference in firm employment between the pre-crisis(2002-07) and post-crisis (2008-16) periods, bounded between [-2,2]. Firm Collateral Match is created as a weighted average of firm-lender collateral match values. Regression is at the firm level. Repeat Loan takes value if firm gets a loan between 2008 and 2016 from a lender with a pre-crisis relationship.

Panel A - OLS

$$\Delta(\text{Employment})_{fci} = \alpha + \beta_1 \text{Repeat Loan}_f + \beta_3 X_f + \gamma_{ci} + \epsilon_{fci}$$

	(1) $\Delta(Emp)$	(2) $\Delta(Emp)$	(3) $\Delta(Emp)$
Repeat Loan	0.183***	0.188***	0.193***
	(0.009)	(0.010)	(0.009)
Observations	23500	23500	23500
County x Industry FE	N	Y	Y
Firm Controls	N	N	Y
Weighted	N	N	N
R^2	0.017	0.101	0.169

Panel B - IV

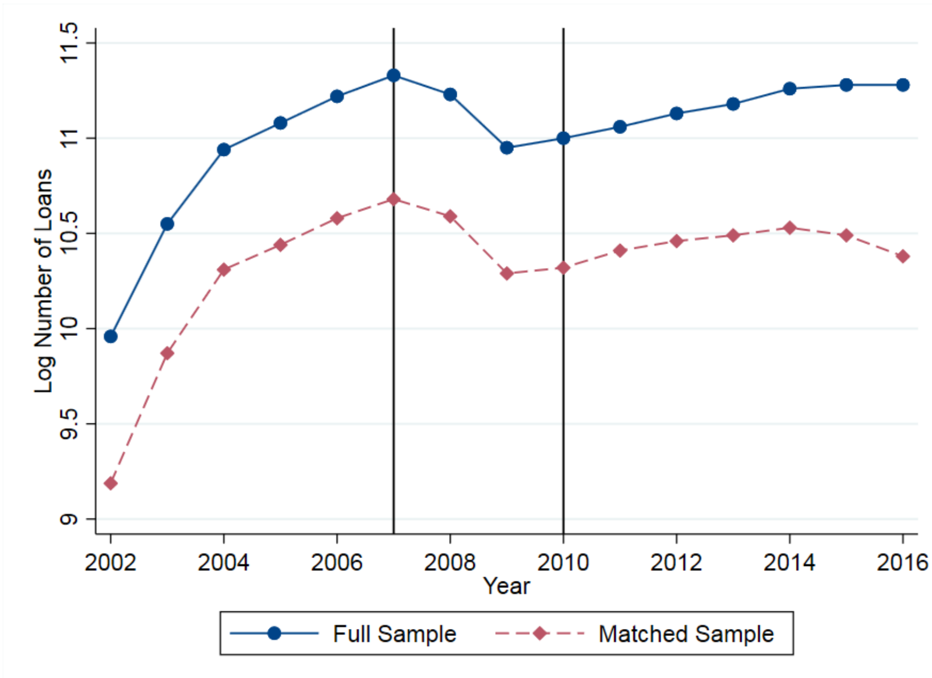
$$\text{Repeat Loan}_f = \alpha + \gamma \text{Firm-Collateral Match}_f + X_f + \delta_{ci} + \epsilon_{fci}$$
$$\Delta(\text{Employment})_{fci} = \alpha + \beta \widehat{\text{Repeat}} \text{ Loan}_f + X_f + \delta_{ci} + \epsilon_{fci}$$

	(1) $\Delta(Emp)$	(2) $\Delta(Emp)$	(3) $\Delta(Emp)$
Repeat Loan	0.217***	0.245***	0.258**
	(0.078)	(0.097)	(0.108)
Observations	23500	23500	23500
County x Industry FE	N	Y	Y
Firm Controls	N	N	Y
First Stage F-stat	332.8	221.8	171.8

Appendix A1 Additional Figures

Figure A1: Match Rates

Figure plots the histogram of average firm cosine similarity to all other borrowers in the economy based on lending between 2004-2007.



Appendix A2 Additional Tables

Table A1: Comparison of LBD to Matched Sample

This table compares the firms in the Longitudinal Business Database with an establishment at some point in Texas to the set of matched UCC-LBD firms. Multi-establishment is a value that takes one if the firm has more than a signle establishment.

	All firms	Matched Firms
Firm Employment (2007)	25.03	70.56
Mean Payroll	1061	3421
Multi-Establishment Firms	0.0524	0.08449
Firm Age (2007)	10.66	13.6
No. of Firms	1044000	93000

Table A2: Distribution of Firm Employment

This table provides the distribution of firm employment for the set of UCC firms matched to the LBD

Percentile	Value
Pseudo 10th pct (mean of 9 - 11)	2.157
Pseudo 25th pct (mean of 24 - 26)	5.107
Pseudo 75th pct (mean of 74 - 76)	33.9
Pseudo 90th pct (mean of 89 - 91)	92.01
No. of Firms	23500

Table A3: Comparison of Firm Characteristics by Match Quality

This table provides summary statistics and comparison across groups for firms with above median and below median firm collateral match.

	Mean(Median1)	Mean(Median2)	Difference	Std. Error
Firm Age	12.47	12.98	-0.5036	0.129
Firm Size	2.552	2.744	-0.1923	0.0197
Multi-Establishment Firm	0.0798	0.1015	-0.0218	0.0037
Multi-Relationship Firm	0.2975	0.3583	-0.0609	0.0061
Avg annual number loans (2002-07)	0.6003	0.8005	-0.2003	0.0142
Avg annual number loans (2008-16)	0.1153	0.2066	-0.0913	0.0072
Exit Rate	0.3692	0.353	0.0162	0.0063

Table A4: Largest Lenders in the Sample

This table includes the 40 largest lenders in Texas including the number of loans originated by the lender between 2002 and 2016.

Lender Name	No. of Loans
Wells Fargo	38736
John Deere	38602
JPMorgan Chase	33233
Caterpillar	24181
US Bancorp	18840
GE Capital	15089
Dell Financial Services	11876
Citibank	11254
Bank Of America	9667
The Frost National Bank	9664
Toyota Motor Credit Corp	8608
CNH Capital America	8156
Compass Bank	7816
TCF National Bank	7766
Kubota	7512
Plainscapital Bank	6960
De Lage Landen	6419
Texas Capital Bank	6200
Holt Cat	5971
Bank Of The West	5827
Automotive Finance Corporation	5809
Prosperity Bank	5779
Amegy Bank	5574
Frost Bank	5505
Komatsu Financial Limited Partnership	5168
First National Bank	5008
ISI Commercial Refrigeration	4770
First Financial Bank	4535
CIT Finance	4368
First State Bank	4325
Sterling Bank	3982
Regions Bank	3886
Bank Of Texas	3642
Texas State Bank	3516
RDO Equipment Co	3346
Nextgear Capital Inc	3286
The American National Bank Of Texas	3191
HPSC Inc	3182
Austin Bank Texas	3099
City Bank	3055

Table A5: Zombie Lending

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firm-lender pairs with a loan between 2002 and 2007. Dependent variable takes is an indicator whether a firm gets a loan in a given year scaled by number of times the firm got a loan in the pre-crisis period. Firm-lender Collateral Match is measured based on a comparison of the firm's real assets to the lender's collateral portfolio.
Sample is restricted for loans made by banks (commercial bank, nonbank-subsidiary of bank holding company, or a credit union). High capital takes value 1 for lenders with above median Tier 1 capital as of December 2006.

$$
\begin{aligned}
\mathbf{y}_{flt} = & \alpha_f + \gamma_l + \delta_t + \beta_{1t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \\
& \beta_{2t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t \times \text{High Capital}_l + \epsilon_{fci}
\end{aligned}
$$

	(1) Scaled Loan	(2) Scaled Loan
Firm-Lender Collateral Match x 2002	-0.442	-0.374
	(0.465)	(0.697)
Firm-Lender Collateral Match x 2003	-0.572**	-0.505
	(0.288)	(0.524)
Firm-Lender Collateral Match x 2004	-0.207	-0.137
	(0.218)	(0.353)
Firm-Lender Collateral Match x 2005	0.041	0.116
	(0.253)	(0.286)
Firm-Lender Collateral Match x 2006	0.076	0.151
	(0.328)	(0.178)
Firm-Lender Collateral Match x 2007	-0.077	0
	(0.299)	

Continued on next page

Table A5 – *Continued from previous page*

	(1) Scaled Loan	(2) Scaled Loan
Firm-Lender Collateral Match x 2008	0.827***	0.904***
	(0.198)	(0.280)
Firm-Lender Collateral Match x 2009	0.643**	0.720*
	(0.252)	(0.409)
Firm-Lender Collateral Match x 2010	0.255	0.333
	(0.304)	(0.536)
Firm-Lender Collateral Match x 2011	-0.253	-0.177
	(0.181)	(0.249)
Firm-Lender Collateral Match x 2012	-0.011	0.066
	(0.197)	(0.246)
Firm-Lender Collateral Match x 2013	0.493**	0.567*
	(0.193)	(0.322)
Firm-Lender Collateral Match x 2014	0.509***	0.579*
	(0.187)	(0.321)
Firm-Lender Collateral Match x 2015	0.093	0.162
	(0.124)	(0.296)
Firm-Lender Collateral Match x 2016	0.157	0.225
	(0.136)	(0.302)
Collateral Match x High Cap x 2002	0.21	0.431
	(0.238)	(0.326)
Collateral Match x High Cap x 2003	0.399***	0.621**

Continued on next page

Table A5 – *Continued from previous page*

	(1) Scaled Loan	(2) Scaled Loan
	(0.145)	(0.245)
Collateral Match x High Cap x 2004	0.039	0.26
	(0.116)	(0.176)
Collateral Match x High Cap x 2005	-0.112	0.106
	(0.132)	(0.152)
Collateral Match x High Cap x 2006	-0.068	0.15
	(0.164)	(0.109)
Collateral Match x High Cap x 2007	-0.217	0
	(0.150)	
Collateral Match x High Cap x 2008	-0.305**	-0.089
	(0.121)	(0.148)
Collateral Match x High Cap x 2009	-0.103	0.114
	(0.141)	(0.200)
Collateral Match x High Cap x 2010	0.049	0.265
	(0.162)	(0.254)
Collateral Match x High Cap x 2011	0.181	0.398**
	(0.133)	(0.168)
Collateral Match x High Cap x 2012	-0.030	0.187
	(0.111)	(0.135)
Collateral Match x High Cap x 2013	-0.251**	-0.032
	(0.109)	(0.161)

Continued on next page

Table A5 – *Continued from previous page*

	(1) Scaled Loan	(2) Scaled Loan
Collateral Match x High Cap x 2014	-0.273**	-0.053
	(0.106)	(0.160)
Collateral Match x High Cap x 2015	-0.124	0.096
	(0.079)	(0.147)
Collateral Match x High Cap x 2016	-0.134	0.086
	(0.085)	(0.150)
Observations	242000	242000
Firm FE	Y	N
Lender FE	Y	N
Year FE	Y	Y
Lender x Year FE	N	N
Firm x Lender FE	N	Y
R^2	0.18	0.189

Table A6: Employment Results

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firms with a loan between 2002 and 2007. Dependent variable is the change is average level of employment between the post-crisis and pre-crisis period. New Loan takes value 1 if the firm gets a loan between 2008 and 2016. Similarity is measured based on real assets pledged by the firm between 2002 and 2007. Regression is at the firm level.

Panel A - OLS

$$\Delta(\text{Employment})_{fci} = \alpha + \beta_1 \text{New Loan}_f + \beta_3 X_f + \gamma_{ci} + \epsilon_{fci}$$

	(1) $\Delta(Emp)$	(2) $\Delta(Emp)$	(3) $\Delta(Emp)$	(4) $\Delta(Emp)$
New Loan	0.240***	0.243***	0.256***	0.272***
	(0.009)	(0.009)	(0.009)	(0.038)
Observations	23500	23500	23500	23500
County x Industry FE	N	Y	Y	Y
Firm Controls	N	N	Y	Y
Weighted	N	N	N	Y
R^2	0.032	0.115	0.184	0.358

Panel B - IV

$$\text{New Loan}_f = \alpha + \beta_1 \text{Firm-Similarity}_f + \beta_1 \text{Firm-Collateral Match}_f + X_f + \delta_{ci} + \epsilon_{fci}$$
$$\Delta(\text{Employment})_{fci} = \alpha + \beta \widehat{\text{New Loan}}_f + X_f + \delta_{ci} + \epsilon_{fci}$$

	(1) $\Delta(Emp)$	(2) $\Delta(Emp)$	(3) $\Delta(Emp)$	(4) $\Delta(Emp)$
New Loan	0.319***	0.338***	0.193**	0.934***
	(0.072)	(0.079)	(0.093)	(0.267)
Observations	23500	23500	23500	23500
County x Industry FE	N	Y	Y	Y
Firm Controls	N	N	Y	Y
Weighted	N	N	N	Y
First Stage F-stat	181.2	152.8	106.8	13.95

Table A7: Employment Results - Dynamic Diff-in-diff

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firms with a loan between 2002 and 2007. Dependent variable is the employment of the firm as of March scaled by the average employment of the firm in the pre-crisis period (2002-07). Similarity is measured based on real assets pledged by the firm between 2002 and 2007. Regression is at the firm level.

$$\text{Scaled Employment}_{fcit} = \alpha + \beta_t \text{Firm Similarity}_f \times \mathbf{1}_t + \beta_2 X_f + \gamma_{cit} + \epsilon_{fci}$$

	(1) Scaled Employment	(2) Scaled Employment	(3) Scaled Employment
Firm Similarity x 2001	−0.099	−0.149**	−0.082
	(0.077)	(0.073)	(0.071)
Firm Similarity x 2002	−0.023	−0.056	−0.027
	(0.052)	(0.054)	(0.052)
Firm Similarity x 2003	−0.038	−0.021	−0.020
	(0.053)	(0.050)	(0.046)
Firm Similarity x 2004	−0.003	0.022	−0.009
	(0.057)	(0.047)	(0.056)
Firm Similarity x 2005	0.083**	0.062	0.111**
	(0.039)	(0.038)	(0.044)
Firm Similarity x 2006	0.040	0.004	0.072
	(0.062)	(0.072)	(0.058)
Firm Similarity x 2007	0.052	0.177**	0.107
	(0.087)	(0.075)	(0.089)
Firm Similarity x 2008	0.233**	0.363***	0.318***
	(0.118)	(0.092)	(0.086)
Firm Similarity x 2009	0.358***	0.332***	0.373***

Continued on next page

Table A7 – *Continued from previous page*

	(1) Scaled Employment	(2) Scaled Employment	(3) Scaled Employment
	(0.129)	(0.106)	(0.102)
Firm Similarity x 2010	0.279**	0.259**	0.209
	(0.134)	(0.125)	(0.128)
Firm Similarity x 2011	0.413***	0.384**	0.404***
	(0.144)	(0.156)	(0.132)
Firm Similarity x 2012	0.411**	0.331**	0.367**
	(0.186)	(0.153)	(0.148)
Firm Similarity x 2013	0.417**	0.179	0.341**
	(0.184)	(0.180)	(0.152)
Firm Similarity x 2014	0.386*	0.309	0.266
	(0.200)	(0.202)	(0.184)
Firm Similarity x 2015	0.326	0.101	0.080
	(0.228)	(0.225)	(0.205)
Firm Similarity x 2016	0.539**	0.217	0.151
	(0.213)	(0.241)	(0.208)
Observations	303000	303000	303000
Year FE	Y	N	N
County x Industry x Year FE	N	Y	N
County x Year Industry x Year FE	N	N	Y
Firm Controls	N	Y	Y
Weighted	Y	Y	Y
R^2	0.047	0.372	0.175

Appendix A3 Data Appendix

Figure A2: Sample UCC Filing

File Number: 20140076446F
Date Filed: 8/12/2014 10:14:00 AM
Elaine F. Marshall
NC Secretary of State

UCC FINANCING STATEMENT
FOLLOW INSTRUCTIONS

A. NAME & PHONE OF CONTACT AT FILER (optional)
Gisella Melendez

B. E-MAIL CONTACT AT FILER (optional)
efiling@wolterskluwer.com

C. SEND ACKNOWLEDGMENT TO: (Name and Address)
CT Lien Solutions
P.O. Box 29071
Glendale, CA 91209-9071

THE ABOVE SPACE IS FOR FILING OFFICE USE ONLY

1. DEBTOR'S NAME: Provide only one Debtor name (1a or 1b) (use exact, full name; do not omit, modify, or abbreviate any part of the Debtor's name); if any part of the Individual Debtor's name will not fit in line 1b, leave all of item 1 blank, check here ☐ and provide the Individual Debtor information in item 10 of the Financing Statement Addendum (Form UCC1Ad)

1a. ORGANIZATION'S NAME					
Best Dedicated, LLC					
OR 1b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)		SUFFIX	
1c. MAILING ADDRESS	CITY	STATE	POSTAL CODE	COUNTRY	
829 Graves Street	Kernersville	NC	28269	USA	

2. DEBTOR'S NAME: Provide only one Debtor name (2a or 2b) (use exact, full name; do not omit, modify, or abbreviate any part of the Debtor's name); if any part of the Individual Debtor's name will not fit in line 2b, leave all of item 2 blank, check here ☐ and provide the Individual Debtor information in item 10 of the Financing Statement Addendum (Form UCC1Ad)

2a. ORGANIZATION'S NAME				
OR 2b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)		SUFFIX
2c. MAILING ADDRESS	CITY	STATE	POSTAL CODE	COUNTRY

3. SECURED PARTY'S NAME (or NAME of ASSIGNEE of ASSIGNOR SECURED PARTY): Provide only one Secured Party name (3a or 3b)

3a. ORGANIZATION'S NAME				
Webster Capital Finance, Inc.				
OR 3b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)		SUFFIX
3c. MAILING ADDRESS	CITY	STATE	POSTAL CODE	COUNTRY
344 Main Street	Kensington	CT	06037	USA

4. COLLATERAL: This financing statement covers the following collateral:

One (1) 2015 Transcraft Combo 48 x 102 Flatbed Trailer, VIN: 1TTF482C5F3843255
One (1) 2015 Transcraft Combo 48 x 102 Flatbed Trailer, VIN: 1TTF482C7F3843256
One (1) 2015 Transcraft Combo 48 x 102 Flatbed Trailer, VIN: 1TTF482C9F3843257
One (1) 2015 Transcraft Combo 48 x 102 Flatbed Trailer, VIN: 1TTF482C3F3843254
financed by Secured Party from time to time, all replacements, accessories, accessions, attachments, returned or repossessed inventory and proceeds thereof including without limitation, cash, accounts, receivables, notes, rental contract rights, chattel paper, documents of title, general intangibles, trade-ins, insurance proceeds, any other obligation due or to become due to the Debtor for payments for any of the described inventory.
#68730-05

5. Check only if applicable and check only one box: Collateral is ☐ held in a Trust (see UCC1Ad, item 17 and Instructions) ☐ being administered by a Decedent's Personal Representative

6a. Check only if applicable and check only one box: ☐ Public-Finance Transaction ☐ Manufactured-Home Transaction ☐ A Debtor is a Transmitting Utility

6b. Check only if applicable and check only one box: ☐ Agricultural Lien ☐ Non-UCC Filing

7. ALTERNATIVE DESIGNATION (if applicable): ☐ Lessee/Lessor ☐ Consignee/Consignor ☐ Seller/Buyer ☐ Bailee/Bailor ☐ Licensee/Licensor

8. OPTIONAL FILER REFERENCE DATA:
NC-0-44455274-48900822

FILING OFFICE COPY — UCC FINANCING STATEMENT (Form UCC1) (Rev. 04/20/11)

A3.1 Data Construction

Sample Restrictions I start with the universe of secured lending in Texas available from the Texas Secretary of State Website. This is a sample of 9.3 million loans. First, I restrict the sample to only new loan originations. This results in a sample of 5.5 million loans. The sample is then restricted to business loan originations (UCC filings are made for both individual debtors (consumer loans) as well as for business loans). This leaves a sample of 2.9 million loans. I then drop loans that were originated before 2002 or after 2016, dropping another 1.2 million observations. Finally, I drop loans without collateral descriptions or missing lender information. Thus, my final sample before matching to the Census data contains 995,657 new loan originations between 2002 and 2016.

Data Cleaning The downloaded raw data is based on the text used in the original UCC filing which is usually unformatted and non-uniform. Therefore, I clean the raw UCC filing information for uniform borrower and lender name. There is a need to clean lender names to track the various loans made by the same lender. Borrower names have to be cleaned for more accurate matching to the Census data.

First, I first remove punctuations and special characters. Then, for lenders with at least 250 loans in the sample, I manually map the various combinations of the names to a common moniker. Through this process, I obtain clean lender names for 75% of the total sample. For the remaining loans, I automate the cleaning by removing common trailing patterns (LLC, Inc, Ltd etc.), expanding abbreviations, and fixing typos in the names to generate common lender names. For bank holding companies with subsidiaries, I match them under a common bank name (for example, loans made by Wells Fargo Bank and loans made by Wells Fargo Leasing as classified as Wells Fargo loans.).

I drop from my sample lending backed by government agencies, such as the Small Business Administration backed loans, or liens held by government agencies such as the Internal Revenue Service. I further drop filings made by UCC filing agencies such as Corporation Service Company (CSC). These services make filings on behalf of their lender customers, and thus makes it impossible to identify the true loan originator.

Similarly, on the borrower side, I clean debtor names by removing common trailing and leading patterns. After merging to the Census data, I drop all firms in FIRE industries (financial, and real estate firms; NAICS code 52 and 53) from the sample. I also drop firms with 0 employment and payroll from the sample.

A3.2 Variable Definitions

Table A8: Variable Definitions

Variable Name	Description
Firm-Lender Collateral Match Quality	Cosine Similarity between collateral pledged by the firm to its relationship lender and collateral of the average borrower of the relationship lender. Similarity based on real assets pledged between 2002-07.
Firm Collateral Match	Firm-level average created by averaging firm-lender collateral match of relationship lenders; weighted by share of lending to the borrower by each lender. $\sum_l$ Firm-Lender Collateral Match Quality$_{fl}$
Firm Similarity	Cosine Similarity between collateral pledged by the firm and the average borrower in the economy; based on real assets pledged between 2002 and 2007
Repeat Loan	Variable that takes value 1 if firm receives a loan in the post-crisis period (2008-16) from a lender with a relationship in the pre-crisis (2002-07) period
New Loan	Variable that takes value 1 if firm receives a loan in the post-crisis period (2008-16)
New Lender	Variable that takes value 1 if firm receives a loan in the post-crisis period (2008-16) from a lender with no pre-crisis relationship
Fraction	Average annual number of loans in the post-crisis period (2008-16) scaled by the average annual number of loans in the pre-crisis period (2002-07)
$\Delta(Emp)$	Average employment change is the second-order approximation of log difference in firm employment between the pre-crisis(2002-07) and post-crisis (2008-16) periods calculated as, $$\Delta(\text{Emp})_f = \frac{\text{Emp}_{f,2008-16} - \text{Emp}_{f,2002-07}}{0.5 \times (\text{Emp}_{f,2008-16} + \text{Emp}_{f,2002-07})}$$

Table A8: Variable Definitions

Variable Name	Description
Scaled Employment	Firm employment scaled by the average annual firm employment in the pre-crisis period (2002-07)
Firm County	For single-establishment firms - county of operation; for multi-establishment firms - County with highest employment share of the firm
Firm Industry	For single-establishment firms - industry of operation; for multi-establishment firms - Industry with highest employment share of the firm; 2-digit NAICS in baseline specification
Firm Size	Log(Employment+1) based on 2007 employment of the firm
Firm Age	Log(Firm-Age+1) based on 2007 age of the firm

A3.3 Comparison to Other Data Sources

CRA data The most commonly used data on small business lending is the data collected under the Community Reinvestment Act (henceforth, CRA data). While there is overlap between the UCC data and the CRA data, there are also significant differences that I highlight below.

First, my data covers bank, finance companies, and other nonbank lenders. The CRA data only covers lending by banks whose assets exceed $1 billion.

Second, my data is collected from UCC filings. Lenders make UCC filings to preserve priority in bankruptcy. The CRA data is collected under the Community Reinvestment Act. The CRA data is used to compute a bank's CRA rating, which is relevant to banks because it determines whether regulators approve proposed mergers and acquisitions. Hence, banks have incentives to report lending in certain areas and there is anecdotal evidence that banks adjust their reported lending according to these incentives.[32] Hence, reporting incentives may affect the quality of the CRA data when used to measure new credit.

[32]See for example, https://www.wsj.com/articles/never-mind-the-ferrari-showroom-bank-regulators-say-this-a-poor-neighborhood-1495108800

Third, the CRA data includes both secured and unsecured credit while UCC filings, by definition, are only made for secured transactions. This means I do not cover unsecured credit to businesses. My understanding is that the main source of unsecured credit are credit cards issued to small businesses.[33]

Fourth, my data identifies new loan originations. The CRA data reports changes in credit limits as new lending even if the change does not result in lending. Moreover, the CRA data counts loan refinancing as new loan originations, while the UCC filings do not. Hence, there is a concern that the CRA may overstate changes in new lending.

Fifth, my data covers all secured lending irrespective of loan size. The CRA data only includes commercial and industrial loans (C&I loans) of less than $1 million. The Government Accountability Office (GAO) has pointed out that the $1 million cut-off (which has remained unchanged since 1992) may undercount lending and that the cut-off in loan size rather than firm size may mismeasure actual lending to small businesses.[34]

Sixth, the CRA data are collected at different levels of aggregation. The UCC data is at the loan-level and be matched to lender and firm characteristics. It also contains information on the underlying collateral. The UCC data, however, does not include information on loan amount. CRA data is collected at the bank-county level and cannot be matched to firm characteristics and does not contain collateral information.

Taken together, the two datasets appear to be complementary. My data has detailed information at the firm-level and regarding collateral but misses information on loan amount and unsecured lending. CRA data includes unsecured lending but cannot be matched at the firm-level and has no information on collateral and larger loans. The CRA data covers banks, while the UCC data includes finance companies and other nonbank lenders. Both datasets may suffer from potential reporting biases. At a minimum, the UCC data provides a way to assess the validity of the widely used CRA data.

Syndicated loan data Another commonly used data source on business lending comes from DealScan. DealScan covers syndicated lending to large businesses. The average size of a syndicated loan in 2016 was $417 million, with 90% of the loans over $10 million. Syndicated loan borrowers are large with mean annual sales of $9 billion in 2016. While syndicated lending is covered by the UCC filings, it only constitutes a small fraction of the number of loans. In 2016, there were about 4,300 syndicated loans made to 2,400 companies.

[33] For credit lines and business credit cards, the CRA calculates the loan amount as the total credit limit of the line. As of 2013, there were 28.3 million business cards. Source - The 2013 Federal Reserve Payments Study, which can be found at https://www.frbservices.org/assets/news/research/2013-fed-res-paymt-study-detailed-rpt.pdf

[34] https://www.gao.gov/reports/GAO-18-312/

For comparison, there were 1.25 million loans made to over 790,000 firms in the U.S. in the universe of UCC data. Syndicated loans account for less than 0.35% of the UCC data.

A3.4 Example Collateral Descriptions

Examples on lien on specific (real) assets

1 john deere 6210 ***utility tractor*** *s/n l06210 p2220681 john deere 620* ***loader*** *s/n w00620 x008907*

one (1) 1999 ford model f350 ***truck*** *vin# 1fdwf36f6xee66983 one (1) 2000 ford mode l f350* ***truck*** *vin# 1fdwf36f2yeb69887 one (1) john deere model 550h* ***crawler dozer*** *s/n t0550hx878428 one (1) ingersoll rand model sd100* ***roller*** *s/n 160632 one (1) ingersoll rand model sd100f* ***roller*** *s/n 160766 one (1) caterpillar model 416c* ***loader backhoe*** *s/n 4zn21386 one (1) dynaweld* ***lowboy*** *vin#4u181djx7y1038915 one (1)* ***freightliner*** *model fl70* ***truck*** *vin# 1fv6hlba4tl601168 one (1) terex model rt230xl 30 ton rough terrain* ***crane*** *s/n 12218 one (1) 1994* ***freightliner*** *model fld12064sd* ***tractor truck*** *vin# 1fuyfsyb8rh763880 one (1) komatsu model br350jg* ***crusher*** *s/n 12 67 one (1) caterpillar model d8r* ***dozer*** *s/n 7xm04399 one (1) caterpillar model 81 5f* ***compactor*** *s/n 1gn00742 one (1) caterpillar model 140h* ***motor grader*** *s/n 9tn008 74 one (1) ingersoll rand model sd100f* ***compactor*** *s/n 160297 complete with all present and future attachments, accessories, replacement parts, repairs, additions and all proceeds thereof.*

1 9 channel dvmr with cd, 250gb hd1 ups ***battery*** *backup 450va capacity1 jvc low light digital color* ***camera*** *with auto iris varifocal lens and outdoor housing and mount*

1. 250 acres of irrigated ***wheat*** *located on section 449, block 1-t, t& no ry. co. survey, sherman county, texas ("section 449");2. 114 acres of dry land* ***wheat*** *located on section 449;3. 2 anhydrous* ***storage tanks*** *located on section 449; and 4. 1 moline* ***irrigation motor*** *and 1 caterpillar* ***motor*** *located on section 449.*

one (1) manitex model m22101 ***hydraulic boom crane*** *s/n 45161 complete with all present and future attachments, accessories, replacment parts, repairs, additions and all proceeds thereof.*

Examples of blanket liens

all ***inventory, equipment, accounts (including but not limited to all health-care -insurance receivables), chattel paper, instruments (including but not limited to all promissory notes), letter-of-credit rights, letters of credit, documents, deposit accounts, investment property, money****, other rights to payment and performance, and* ***general intangibles*** *(including but not limited to all software and al l payment intangibles); all attachments, accessions, accessories, fittings, increases, tools, parts, repairs, supplies, and commingled goods relating to the foregoing property, and all additions, replacements of and substitutions for all or any part of the foregoing property; all insurance refunds relating to the foregoing property; all good will relating to the foregoing property; all records and data and embedded software relating to the foregoing property, and* ***all equipment, inventory and software*** *to utilize, create, maintain and process any such records and* ***data on electronic media****; and all supporting obligations relating to the foregoing property; all whether now existing or hereafter arising, whether now owned or hereafter acquired or whether now or hereafter subject to any rights in the foregoing property; and all products and proceeds (including but not limited to all insurance payments) of or relating to the foregoing property. including but not limited to all business assets of mdj floorings, inc. located at 10641 harwin dr. #500, houston, texas 77036; and wherever located.*

all of debtor's ***accounts, notes, drafts, acceptances, instruments, chattel paper and general intangibles****, and all guaranties and suretyship agreements relating thereto and all security for the payment or performance thereof, whether now existing or hereafter arising; all proceeds, monies, income, benefits, collections and products thereof and thereon and attributable or accruing thereto; all goods which give rise or may give rise thereto, including, without limitation, all re turned or repossessed goods and other goods the sale or delivery of which gave rise or may give rise to any of such* ***accounts, notes, drafts, acceptances, instruments, chattel paper or general intangibles****, including the right of stoppage in transit, and the products and proceeds thereof; and all rights of debtor, whether or not earned by performance, under contracts to sell or lease goods or render services, and all proceeds thereof.*

all debtors assets and properties wherever located, including without limitation ***all equipment*** *of any kind or nature,* ***all vehicles, vehicle parts and in-***

ventory *now owned or hereafter acquired, without limitation, purchase money inventory, the purchase of which was financed or floorplanned by dealer services corporation for debtor of whatever kind or nature, and all returns, repossessions, exchanges, substitutions, attachments, additions, accessions, accessories, replacements , and proceeds thereof;* ***all accounts receivable, chattel paper, and general intangibles*** *now owned or hereafter acquired by debtor together with the proceeds thereof; all of debtors documents, books and records relating to the forgoing.*

all ***inventory, chattel paper, accounts, contract rights, equipment, general intangibles and fixtures****; together with following specifically described property:* ***furniture and machinery****; whether any of the foregoing is owned now or acquired later; all accessions, additions, replacements and substitutions relating to any of the foregoing; all records of any kind relating to any of the foregoing; all proceeds relating to any of the foregoing (including insurance, general intangibles and other account proceeds)*

Appendix A4 Dictionary of Real Assets

adapter, aircraft, airframe, alarm, ale, alloy, alum, aluminum, amplifier, antenna, apple, appliance, arrow, art, asphalt, atv, audio, auto, automobile, automotive, avionics, axle, backhoe, bailee, ball, band, barrel, basket, battery, beam, bed, beef, bell, belt, beverage, bike, bin, blade, blast, blaster, blender, blinds, blocks, blower, bluetooth, boat, boiler, bolt, bottle, box, bracket, brakes, brass, bread, bridge, broom, brush, buckets, buggy, bulls, burner, bus, bush, cab, cabinet, cable, cad, cage, calves, camera, canopy, car, carbon, card, carpet, carriage, carriers, cars, cart, cartridge, casing, cassette, cattle, cell, cellular, cement, chains, chair, chamber, charger, chassis, chemical, chiller, chip, chipper, chisel, chrome, chute, circuit, clamp, cleaner, clothing, coil, coin, compactor, components, compressor, computer, concrete, condenser, conditioner, condominium, cone, connector, console, container, controller, converter, conveyors, coolant, cooler, copier, cord, cordless, corn, cotton, counters, coupler, cows, cpu, craft, crane, crawler, crop, crude, crusher, cultivator, cup, cutter, cycle, cylinder, deck, dental, desk, desktop, diamond, diesel, dig, digger, digital, dishes, dishwashers, disk, dispenser, dock, dodge, dome, door, dozer, drain, drapes, drawers, drill, drilling, drink, drives, drugs, drum, dryer, duct, dumbbell, electric, electrical, electronic, elevator, embroidery, encumbrancer, engine, ethernet, excavator, exhaust, exploration, extinguisher, extraction, extractor, fab, fabric, fans, farm, fax, feed, feeder, fence, fertilizer, fiber, fiberglass, film, filters, flatbed, fleet, flex, flight, floor, floppy, fluid, forklift, forks, frame, freezer, freight, freightliner, fryer, fuel, furance, fuse, gas, gasoline, gator, gauge, gear, generator, genset, gin, glass, gold, golf, goods, grain, granite, graphic, grill, grinder, gun, hammer, handpiece, handsets, hardware, harvester, hat, hauler, hay, header, headsets, heater, heating, highway, hoe, hog, hopper, hose, hustler, hvac, hydraulic, hydro, hydrocarbons, ice, imagerunner, imaging, incinerators, inkjet, inverter, iron, irrigation, jack, jaws, jet, jewelry, keyboard, kitchenware, knife, lamb, laminator, lamp, land, laptop, laser, laserjet, latex, lathe, laundry, lcd, lead, leather, led, lever, lift, lighting, lights, liquid, liquor, livestock, loader, lock, log, loop, lots, lowboy, lube, macbook, magnet, mast, medicine, merchandise, mercury, metal, meters, microfiche, microfilm, microwave, milk, milling, mineral, mining, mirror, mixer, mobile, modem, modular, monitor, motor, motorgrader, mouse, mower, mud, needle, network, nylon, oak, oil, oilfield, optical, optiplex, orange, oven, oxygen, package, pad, paint, paintings, pallet, panel, pencil, peripheral, petroleum, phone, photograph, pickup, pipes, pivot, plane, plant, planter, plasma, plat, plate, platinum, plow, plumbing, pneumatic, pool, ports, pot, poultry, print, printer, printing, probing, propane, propeller, pulse, pump, quad, rack, radio, rafts, rail, railroad, rake, rams, ranch, recorder, refrigerator, rice, rings, ripper, robot, rock, rod, roll, rollers, roof, rotary, router, rubber, saddle, sand, sander, sapphire, satellite, savings, scale, scanner, scanning, scissor, scraper, screens, screw, scrubber, seats, seed, sensor, server, sewer, shaft, sheets, shelf, shell, shifter, ship, shipment, shippers, shipping, shredder, shuttle, signage, silver, sink, skid, skidder, skidsteer, software, solar, spindle, sprayer, sprinkler, ssd, stabilizer, stacker, stainless, stationary, steam, steel, steer, stone, stool, storage, store, stoves, strap, stream, stripper, strobe, structures, swap, sweeper, swing, switchboards, systems, table, tablet, tank, tanker, tape, taps, technology, telehandler, telephone, telescopic, television, tents, terminal, thermal, thumb, timber, tire, titan, titles, tooling, tools, tower, track, tractor, trailer, trailmobile, trainer, transformers, transmission, tray, treadmill, trench, trimble, trimmer, trolley, truck, trucking, trunk, trust, tube, tubing, tv, ultrasonic, ultrasound, upholstery, vacuum, valve, van, vehicle, ventilating, vessel, wagon, walls, walnut, ware, warehouse, washer, welding, wheat, wheel, wheeler, whet, widescreen, wifi, wind, window, wine, wing, wire, wireless, wiring, wood, wrench,

Appendix A5 Results on Cash Flow Pledgeability

Up until now, this paper has focused on firms with real assets, while ignoring loans with blanket lien pledges. In this section, I retain the full sample of loans. As described in Lian and Ma (2019) and Drechsel (2019), there is a great prevalence of earnings based constraints in syndicated lending. While small business loans do not generally contain covenants, blanket-lien claims that provide rights to all firm assets and cash flows serve a similar purpose by linking borrower cash-flow prospects to borrowing constraints.

I split the type of collateral pledged by firms into two categories - loans where the borrower pledges rights to firm assets (asset pledgeability), and loans wherein the firm pledges the rights to firm cash flows (cash flow pledgeability). When a firm pledges real assets such as equipment, machinery, and tools, it gives the lender the right to seize and liquidate the *particular* piece of asset in case of default. On the other hand, when a lender places a blanket lien on all of the firm's assets and income sources (such as accounts receivables, inventory, etc.) or controls cash flows (through a lien on deposit accounts), the lender has the right to every asset of the firm.[35] Parallelly, this could be considered a mapping between fixed and floating liens as in Cerqueiro, Ongena, and Roszbach (2019) and Cerqueiro, Ongena, and Roszbach (2016)

Differences in firm real assets are driven by the line of business of the firm. Business needs reduce the flexibility in substitution of collateral within real assets. For example, while uncommon in the economy, tower cranes are required for construction of high-rise buildings and cannot be substituted for by other types of cranes or machinery. However, firms can additionally pledge rights to cash flows to compensate for lack of real assets.

The separation of asset and cash flow pledgeability in my case can be mapped to the characterization in Diamond, Hu, and Rajan (2019).[36] They consider two characteristics of collateral - liquidity (which provides lenders the right to repossess and sell the asset), and pledgeability (which provides creditors control rights to the firm). In my case, real assets serve to reduce lender losses through asset resale while blanket liens and cash-like assets provide the lender control rights over cash flows generated by the business.

To separate cash flow pledgeability, I consider all loans with blanket liens on firm assets, as well as loans that independently pledge cash-like assets such as deposit accounts, accounts receivables, chattel paper, inventory, contract rights, intangibles, claims on tax refunds etc. Loans are considered to be "real asset" loans if the lien is only on specifically identified assets

[35] As in Ivashina, Laeven, and Moral-Benito (2019), I do not include inventory and accounts receivables as cash-flow lending

[36] Donaldson, Gromb, and Piacentino (2019) argue cash-flow pledges are required to prevent a dilution of lender claims.

including cash flow from proceeds of the asset.

In this section, I disentangle the effect of pledging rights to cash flows (interchangeably, blanket liens) on future firm outcomes. Theoretically, the relationship could go in either direction. Since blanket liens provide rights to all firm assets, it increases creditor control and potential recovery in case of default. However, given the endogenous nature of the pledge, safe firms may be less willing to pledge away the rights to all assets. Additionally, lenders may require riskier firms to pledge greater collateral under the ex-post theories. This is, therefore, an empirical question.

To disentangle the mechanism, I run the following OLS regression:

$$\mathrm{y}_{fci} = \alpha + \beta \text{Cash-Pledge}_f + X_f + \delta_{ci} + \epsilon_{fci} \tag{16}$$

where y_{fcit} is either an indicator variable that takes value of one if the firm f in county c, industry i gets a loan after 2007 and zero otherwise, or the number of loans to the firm after 2007 scaled by the number of loans to the firm in the pre-crisis period. The sample is restricted to firms with at least one loan in the pre-crisis period (2002-07).

Here Cash-Pledge takes a value of zero if the firm pledges real assets when taking out loans in the pre-period and a value of one if it pledges blanket liens or cash assets in all its pre-crisis loans. Regression includes firm controls such as size and age as well as controls of local demand at the county-industry (2-digit NAICS) level.[37]

Table A9 presents the results of regression specification in Equation 16. The outcome variable in Columns 1-3 is an indicator for new loan, and Columns 4-6 is fraction of post-crisis to pre-crisis lending. Panel A provides results for lending from pre-crisis relationship lenders of the firm. Panel B provides results for total lending to the firm including lending from new, non-relationship lenders.

Column 1 of Panel A indicates that firms that pledge blanket liens assets are 15.7% less likely to get a loan from their relationship lenders, compared to an unconditional probability of getting a new loan that is 23%. In Columns 2 and 3, I include controls to understand whether lending differences are driven by alternate channels. In Column 2, I include county and industry fixed effects to control for local demand. This reduces the magnitude of the coefficient from 15.7% to 13.1%. In Column 3, I further include firm controls for size (firm employment) and age (time from establishment) as of 2007. Size and age control for observable differences in firm characteristics that may explain differences in outcomes. Including controls changes the coefficient to 11.2%, still highly economically significant.

In Panel B of Table A9, I study the extent to which firms are able to substitute to new

[37] Results robust to extending the industry categorization upto 4 digit NAICS industries.

lenders. While a long literature in banking has shown the importance of lending relationships for small businesses, if firms are able to substitute for credit drop through substitution to new lenders, credit supply shocks should not have real outcomes. To test for firms ability to substitute, I study total firm lending in Panel B.

Column 1 of Panel B indicates that firms that pledge blanket liens assets are 18%. less likely to get a loan in the post period while the unconditional probability of getting a new loan is 53.46%. In Columns 2 and 3, I include controls. In Column 2, I include county and industry fixed effects to control for local demand. This reduces the magnitude of the coefficient from 18% to 16.3%. In Column 3, I further include firm controls for size (firm employment) and age (time from establishment) as of 2007. Including controls changes the coefficient to 12.7%.

Table A10 I show that loan outcomes are not driven by differential lender matching. If firms that pledge blanket liens were more likely to have borrowed from lenders that suffered during the financial crisis, the difference in firm outcomes could be explained by differences in lender behavior rather than differences in firm collateral. I show that including lender controls, and studying the differential effect on firms of the *same* lender leads to qualitatively identical results.

For each firm-lender pair, firms that pledge blanket liens to their lender are 7.8% less likely to get a loan from that lender. Controlling for the lender decreases the effect to 7.5%. Additional controls for county and industry of borrower as well as firm controls reduces the magnitude to 5.2%.

Finally, Table A11 presents the within-firm specification for firms that pledge both real assets and blanket liens. This controls for any association between firm risk and likelihood of pledging blanket lien. Results in Column 3 of Table A11 suggest that lending to the same firm from a lender that has been pledged a blanket lien in the pre-crisis period is 3.6% lower.

Table A9: Firm Lending based - Split by Real Assets vs. Blanket Liens

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firms with a loan between 2002 and 2007. Dependent variable takes a value of 1 if the firm gets a new loan after 2008 (columns 1-3), or the average annual lending to the firm between 2008-16 as a fraction of average lending between 2002 and 2007 (columns 3-6). Cash-only is a variable that takes value 1 if the firm only pledges cash-like assets or blanket liens in the pre-crisis period. Regression is at the firm level.

$$y_{fci} = \alpha + \beta_1 \text{Blanket Liens}_f + \beta_3 X_f + \gamma_{ci} + \epsilon_{fci}$$

Firm controls include the firm size measured by employment, and firm age in 2007.

Panel A - Relationship Lending

	Loan			Fraction		
	(1)	(2)	(3)	(4)	(5)	(6)
Cash-Only	−0.157***	−0.131***	−0.112***	−0.051***	−0.040***	−0.031***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Observations	44500	44500	44500	44500	44500	44500
County x Industry FE	N	Y	Y	N	Y	Y
Firm Controls	N	N	Y	N	N	Y
R^2	0.033	0.111	0.131	0.014	0.091	0.104

Panel B - Total Lending

	Loan			Fraction		
	(1)	(2)	(3)	(4)	(5)	(6)
Cash-Only	−0.180***	−0.163***	−0.127***	−0.123***	−0.096***	−0.043***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Observations	44500	44500	44500	44500	44500	44500
County x Industry FE	N	Y	Y	N	Y	Y
Firm Controls	N	N	Y	N	N	Y
R^2	0.031	0.093	0.137	0.008	0.074	0.119

Table A10: Firm-Lender Lending - Split by Real Assets vs. Blanket Liens

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firm-lender pairs with a loan between 2002 and 2007. Dependent variable takes a value of 1 if the firm gets a new loan after 2008 (columns 1-4), or the average annual lending to the firm between 2008-16 as a fraction of average lending between 2002 and 2007 (columns 5-8). Cash-only is a variable that takes value 1 if the firm only pledges cash-like assets or blanket liens in the pre-crisis period. Regression is at the firm-lender level.

$$y_{flcit} = \alpha + \beta_1 \text{Cash-Only}_f + \beta_3 X_f + \delta_l + \gamma_{cit} + \epsilon_{flcit}$$

Firm controls include the firm size measured by employment, and firm age in 2007.

Panel A - New Loan

	(1) Loan	(2) Loan	(3) Loan	(4) Loan
Cash-Only	−0.078***	−0.075***	−0.065***	−0.052***
	(0.013)	(0.007)	(0.007)	(0.006)
Observations	74000	74000	74000	74000
Lender FE	N	Y	Y	Y
County x Industry FE	N	N	Y	Y
Firm Controls	N	N	N	Y
R^2	0.008	0.138	0.174	0.179

Panel B - Fraction of Loans

	(1) Fraction	(2) Fraction	(3) Fraction	(4) Fraction
Cash-Only	−0.047***	−0.044***	−0.037***	−0.027***
	(0.009)	(0.005)	(0.005)	(0.004)
Observations	74000	74000	74000	74000
Lender FE	N	Y	Y	Y
County x Industry FE	N	N	Y	Y
Firm Controls	N	N	N	Y
R^2	0.007	0.130	0.166	0.172

Table A11: Real Assets vs. Blanket Liens - Within-Firm

This table includes firms in Texas between 2002 and 2016. Sample is restricted to firm-lender pairs with a loan between 2002 and 2007, and firms that borrow from multiple lenders. Dependent variable takes a value of 1 if the firm gets a new loan after 2008. Cash-only is a variable that takes value 1 if the firm pledges cash-like assets or blanket liens to the lender in the pre-crisis period. Regression is at the firm-lender level.

	(1) Loan	(2) Loan	(3) Loan
Cash-Only	-0.065^{***}	-0.052^{***}	-0.036^{***}
	(0.016)	(0.014)	(0.009)
Observations	38500	38500	38500
County x Industry FE	Y	N	N
Firm Controls	Y	N	N
Firm FE	N	Y	Y
Lender FE	N	N	Y
R^2	0.072	0.349	0.501