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

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QUALITATIVE RESULTS PRESENTED FOR OUTPUT AWAITING CENSUS DISCLOSURE REVIEW
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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 specializing 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 found 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.

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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 advantage or lender expertise. These advantages become consequential in a downturn. As borrower default probabilities increase, 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 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 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 the 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 among the first to create a quasi credit registry for the U.S. with 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, 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 the 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 than diversified lenders. For identification, therefore, I exploit variation in credit supply to the *same* firm for multi-relationship borrowers, as well as 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 the measure is to capture the extent of specialization of a lender in the collateral of the borrower. The assumption underlying this measure is that lenders have greater expertise in collateral that

[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

occurs more frequently in their portfolio, after accounting for the aggregate availability of the collateral in the economy.[5] Using loans originated between 2002 and 2007 (pre-crisis period), each firm-lender pair is assigned a 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. Roughly 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 in understanding whether Firm A is more likely to receive credit from Financial Federal Credit in the downturn than from Frost National Bank.

To identify the causal effect of lender 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 14.3% 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 inclusion of controls for lender specialization in an industry, and by looking across borrowers within the same lender-industry cell. Controlling for lender specialization in the 6-digit NAICS industry of the borrower, a one standard deviation in Firm-Lender Collateral Match increases

[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

the probability of receiving a new loan by 2.6% which is equivalent to 13% of the mean probability of receiving a loan.

Second, I test whether lending advantages are driven by specialization in collateral or firm-specific knowledge, specifically soft information. As discussed extensively in the banking literature, lenders accumulate private information about the firm during the course of business, which may affect lending decisions. Thus, I include proxies for 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% higher likelihood of getting a new loan compared to 14% 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 the idea 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 ex-post ability to redeploy the collateral) 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 project cash flows) while finance companies lend against collateral values. For some lenders in the sample, specifically captive finance companies, increasing collateral sales and value may be the primary motivation for lending. These differences do not explain the observed specialization patterns.

Second, lenders may concentrate borrowing to prevent writing down of bad loans, by lending to otherwise insolvent borrowers (i.e. zombie lending). Distressed banks may re-allocate 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. I show, however, that low-capitalization banks, who are most likely to have zombie lending motives, do not behave differently from high-capitalization banks.

Third, lenders may be worried about fire sales losses and concentrate their portfolio on assets least 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. Under the fire-sales hypothesis, lenders would be less likely to lend to distressed industries (that face greater fire-sale discounts) even if they have expertise in the collateral. However, I show that changes in Firm-Lender Collateral Match Quality leads to a similar effect on change in lending for firms in distressed industries.

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 its relationship lenders. 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 a new lender. Total lending to the firm, therefore, is a function of the firm's lending from relationship lenders (determined by match quality to those lenders) plus lending from new sources which is determined by overall commonality of the firm's collateral. Finally, I show that firm's match quality and overall asset commonality can have real implications affecting firm employment drop during, and the pace of recovery following the financial crisis. A one standard deviation increase in firm collateral similarity increase the average level of post-crisis firm employment by 3.36%

A few caveats are in order. While I observe the extensive margin of credit allocation, data restrictions prevent the observation of either loan quantity or pricing. Thus, I consider the extensive margin results to be a lower bound on the true decline in credit. On 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 full 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 would avoiding concentrating their lending portfolio. However, the argument relies on banks having equal expertise in all sectors of the economy.[6] 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)).[7]

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 decision, how such specialization changes when lenders are constrained, and the important economic consequences of lender specialization.

Second, my paper relates to the literature on matching between borrowers and lenders 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 this approach, I estimate the quality of match between borrowers and lenders and document the consequences of change 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,

[6] 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

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

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.[8] Importance of collateral has further been documented in the empirical literature.[9] I add to the literature on 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 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)).[10] 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. Overall, asset commonality has implications for real outcomes.

[8]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)).

[9]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)

[10]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))

Finally, my paper relates to the literature on credit supply during and in the aftermath of the financial crisis. The literature argues that change in credit supply played an important role in triggering and amplifying the financial crisis.[11] 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.[12] 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.[13] Furthermore, I contribute to the literature documenting the real effects of credit supply shocks with detailed information link small business lending to employment outcomes.[14]

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

[11] 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.

[12] 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.

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

[14] 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)

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.[15] 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.[16] Furthermore, properties with titles, such as automobiles, boats, and airplanes, generally do not require state-level UCC filings for liens.[17] Any other collateral pledged by borrowers must 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.[18] 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.

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

[16] 63% of loans to small and medium-size businesses are backed by non real-estate collateral - see Calomiris, Larrain, Liberti, and Sturgess (2017)

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

[18] List of largest lenders in the sample available in Appendix A2

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).

However, 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. Thus, 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 (2002-2007) before the crisis, and a nine year crisis and recovery period (2008-2016) 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 descriptions 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.[19]

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 ($\sim$ 95%) 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 like 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 comparators to aid with the matching.[20] 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.[21] 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

[19] 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.

[20] See COMPGED and SPEDIS functionality in SAS

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

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.

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.[22] 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.[23] To retain loans/firms with real assets, I create a dictionary of words for all real assets (equipment and machinery) from my sample, and retain descriptions with just these 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.[24] 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

[22] 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).

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

[24] 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.

information about a lender's specialization if present in it's portfolio.

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 a full set 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

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

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[25] 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

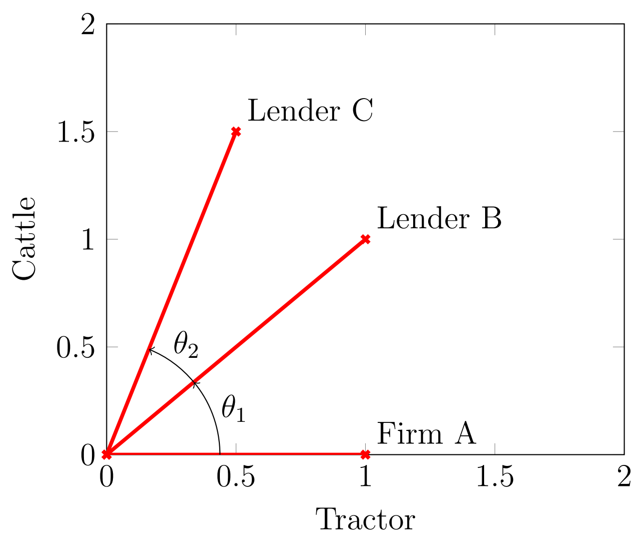
[25] Previously used in the finance literature to measure industry similarities in Hoberg and Phillips (2010) and Hoberg and Phillips (2016) and to calculate the impact of patents in Kelly, Papanikolaou, Seru, and Taddy (2018).

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

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.



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 (2002-2007). 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. The variable is demeaned by the mean firm-lender collateral match quality to capture the relative match between the borrower and lender.

Statistics on the firm-lender collateral match quality values are provided in Panel B of Table 1. The standard deviation of the firm-lender match quality is 22.78%. The 10th percentile of the distribution is -0.2531 and 90th percentile in 0.2765.

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 who 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 lender, 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 1 two distributions. In the solid line, I plot the standardized 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 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.

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

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

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 1.9%. This is equivalent to 9.6% of the mean. In column 2, I include controls for county and industry[26] of the borrower to control for differences in demand. With the control, a one standard deviation increase in firm-lender collateral match increases the probability of getting a repeat loan by 10.84% above unconditional mean. In Column 3, firm controls on size and age are included to control for firm-level differences. This changes the effect to an increase in 10.26% of mean.

In Columns 4-6, I restrict the sample to firms with multi-banking relationships in the

[26] 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.

pre-crisis period. Column 4 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 an increase 2.34% of equivalent 11.87% of mean. Including firm fixed effects in Column 5 further increases the effect to 2.73% 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 2.82%. This is equivalent to 14.3% of the mean probability of new loan.

Dynamic Difference-in-Difference

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

$$\begin{aligned} \mathbf{y}_{flt} = & \alpha_f + \gamma_l + \delta_t + \beta_1 \text{ Firm-Lender Collateral Match}_{fl} \\ & + \beta_{2t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \epsilon_{fci} \end{aligned} \tag{2}$$

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. These results are currently under review at the Census. I note that 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 2014.

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 test for 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.[27]

To separate lender specialization in an industry from its collateral specialization, I conduct two tests.

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

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.

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

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. Collateral retains its statistical significance upon including lender, industry fixed effects.

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 2,4,6 digit NAICS level.

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.

While these measures proxy for soft information, they 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 14.3% above mean. In Column 2, I include a measure of the average annual number of loans between the borrower and lender in the pre-crisis period. In Column 3, I use share of lending from the relationship lender as a control for relationship strength. In Column 4, I include, as a control, the number of years since the last loan to the borrower. Finally, in Column 5, I include both the number of loans and time from the last loan as a control.

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. The observed matches for new borrowers is concentrated in the right tail of the random firm-lender pair match scores. 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 all 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 significant difference across banks[28] 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 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 2.5% for non-captive lenders and 6.6% 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.

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

I test for both 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 preventing 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 are presented in Table 7. Results currently under review at the Census. Results show that there are no statistically significant differences in specialization across lenders with high and low Tier 1 capital.

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 specialized collateral. 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.[29]

Results are presented in Table 8. 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.

[29]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.

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 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 9. 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 lender, 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. 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

$$\text{Repeat Loan}_f = \alpha + \beta_{\mathbf{1}} \text{Firm Collateral Match}_f + X_f + \epsilon_f \tag{10}$$

Results are provided in Panel A of Table 10. Columns 1-3 present result for the dependent variable dummy that takes value 1 if firm gets a new loan between 2008 and 2016. In Column 1, without any firm-level controls, a one standard deviation increase in firm collateral match increases lending from relationship lenders by 8.13% which is equivalent to 27% of the mean. Adding local county and industry fixed effects changes the magnitude of the effect to 7.64%. 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 6.9%

In Columns 4-6, the dependent variable is the average annual number of new loans in the post-crisis period scaled by the average annual number of loans in pre-crisis period. In Column 4, a one standard deviation increase in firm collateral match increases fraction of lending from relationship lenders by 2.4% equivalent to 16.1% of the mean. In Column 5, after the inclusion of county,industry fixed effects, a one standard deviation increase in firm collateral match increases fraction of lending from relationship lenders by 2.2%. Adding firm-level controls reduces the magnitude to 2.0%

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 11, I test borrower substitution to new lenders against the measure of firm similarity.

$$\text{New Lender}_f = \alpha + \beta_{\mathbf{1}}\text{Firm Similarity}_f + X_f + \epsilon_f \tag{11}$$

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 11, 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% equivalent to 8.31% of the mean probability of loan from a new lender. 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 highly significant.

Finally, I study the effect on total lending against firm similarity. In Figure 3, 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 11 presents effect of firm collateral on total lending. A one standard deviation increase in firm similarity increases the total probability of receiving a loan in the post-crisis period by 5.73% equivalent to 9.3% of the mean. Inclusion of county-industry fixed effects and firm controls in Columns 2 and 3 reduces the magnitude to 5.56% and 4.61% 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 4, analogous to credit, I plot firm employment against Firm Similarity which compares the firm's collateral to the weighted average lender in the sample. I note that firms with above and below median firm similarity have parallel growth rate in employment between 2002 and 2007. After the start of the crisis, however, firms with below median similarity see a greater drop in total employment during the crisis and a slower recovery from the crisis.

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

$$\begin{aligned} \text{New Loan}_f &= \alpha_1 + \gamma \text{ Firm Similarity}_f + X_f + \epsilon_{fci} \\ \Delta(\text{Employment})_f &= \alpha_2 + \beta \text{New }\hat{\text{Loan}}_f + X_f + \epsilon_{fci} \end{aligned} \tag{12}$$

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 12 presents the results for employment. In Panel A, I present the OLS results. A one standard deviation increase in probability of receiving a loan in the post-period increases employment at the firm by 11.67%. The IV produces results of similar magnitude at 15.2% growth for one standard deviation increase in new loan.

Finally, I estimate a dynamic version of the effect of collateral on 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.[30] 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.

Table 13 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 3.57% above the firm's pre-crisis mean level. 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 (2015). Results can be visualized in Figure 5.

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 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 6, 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 2008, the firm-lender collateral match is successively increasing till about 2013 after which it falls back again. This suggests that the level of firm-collateral matching required for credit extension is most important in a downturn.

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

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

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

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 7 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.

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6 Figures

Figure 1: Firm-Lender Collateral Match

This figures plots the kernel density for standardized scores of Firm-Lender Collateral Match Quality. Sample includes firms in Texas with at least one loan in the pre-crisis (2002-07) period.

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 borrower and lender in the pre-crisis period.

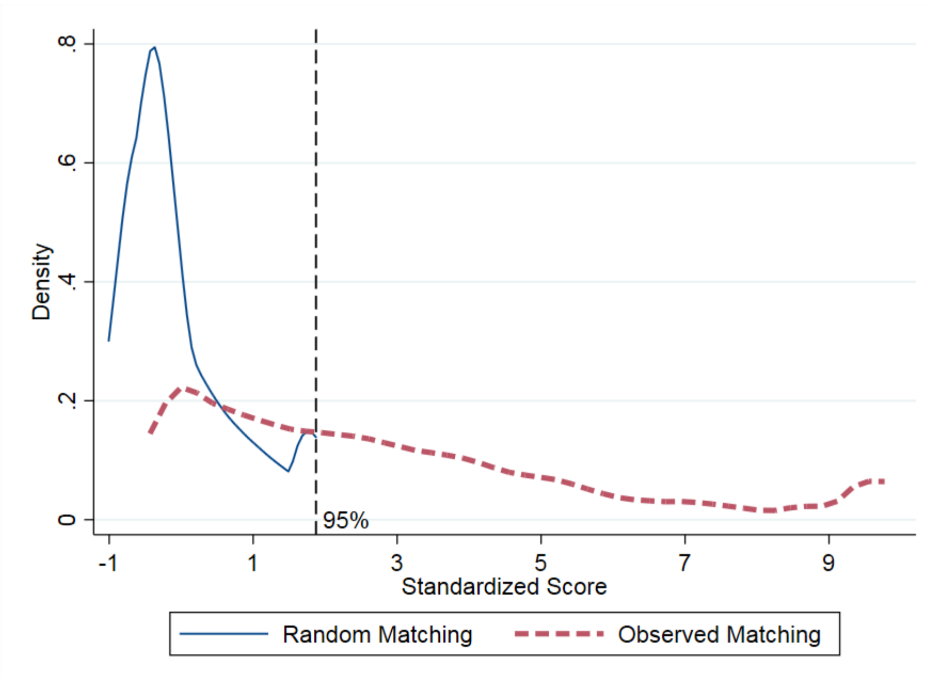


Figure 2: Firm-Lender Collateral Match Quality

This figure plots lending to firm-lender pairs with a lending relationship between 2002-2007. 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 2002-2016.

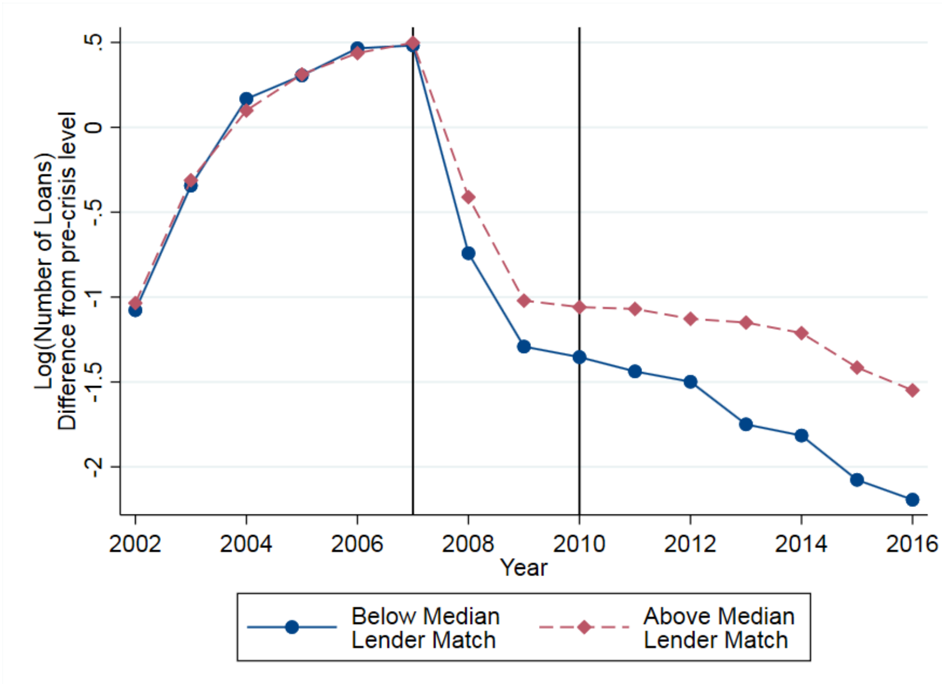


Figure 3: Firm Similarity - Total Lending

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. Sample includes firms in Texas with at least one loan in the pre-crisis (2002-07) period. Firms are separated into borrowers with above and below median similarity. Total annual firm lending is plotted.

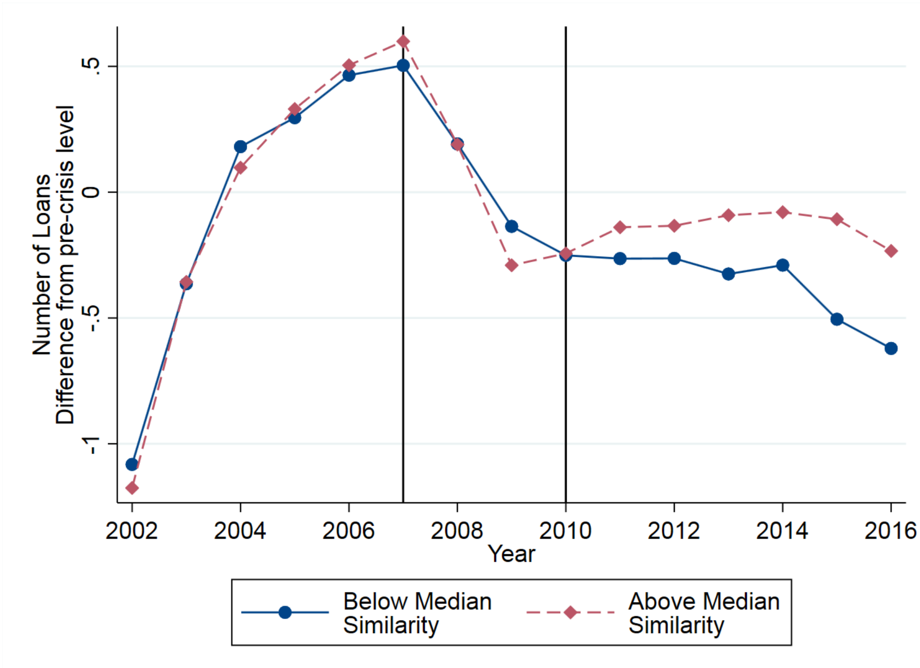


Figure 4: Firm Employment

Firm Similarity is a measure of collateral match between the borrower and (weighted) average of all lenders in the sample. Average employment for firms with above and below median firm similarity is plotted. Employment is demeaned by the average employment at the firm in the pre-crisis period (2002-07).

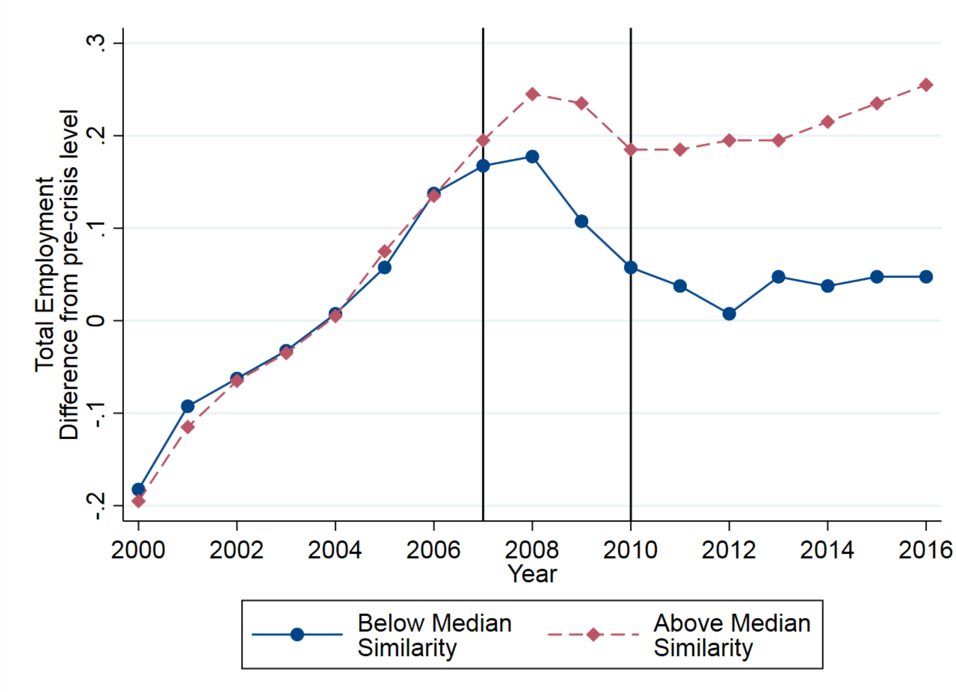


Figure 5: Regression Betas

Coefficients from the following regression specification are plotted -

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

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. Regression is weighted by the firm employment in 2007.

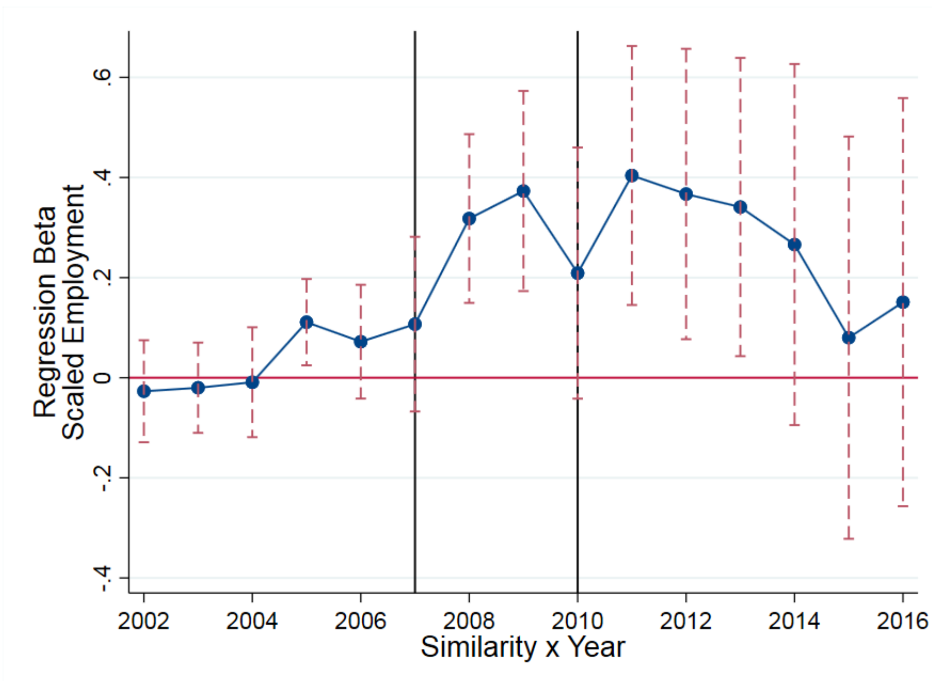


Figure 6: Aggregate Trends

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

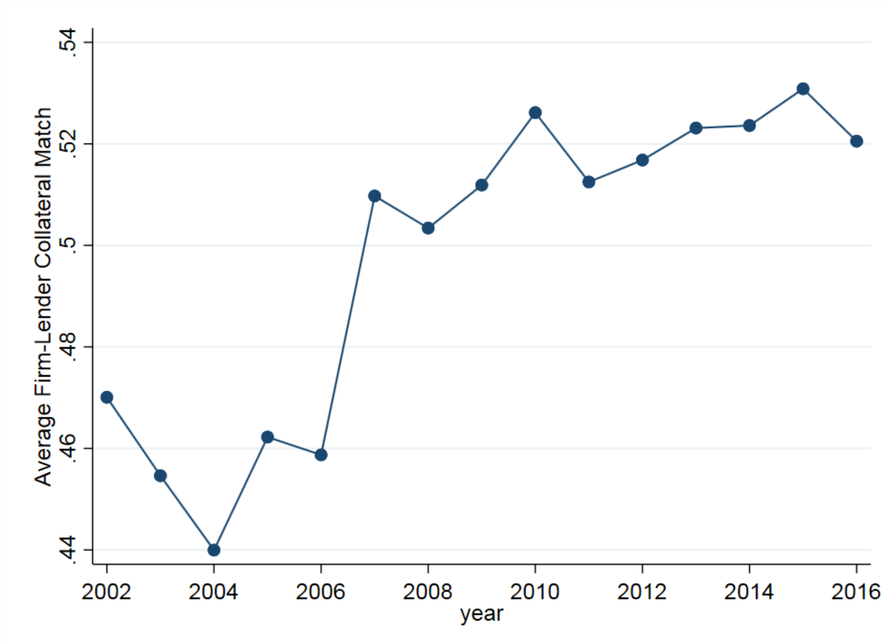
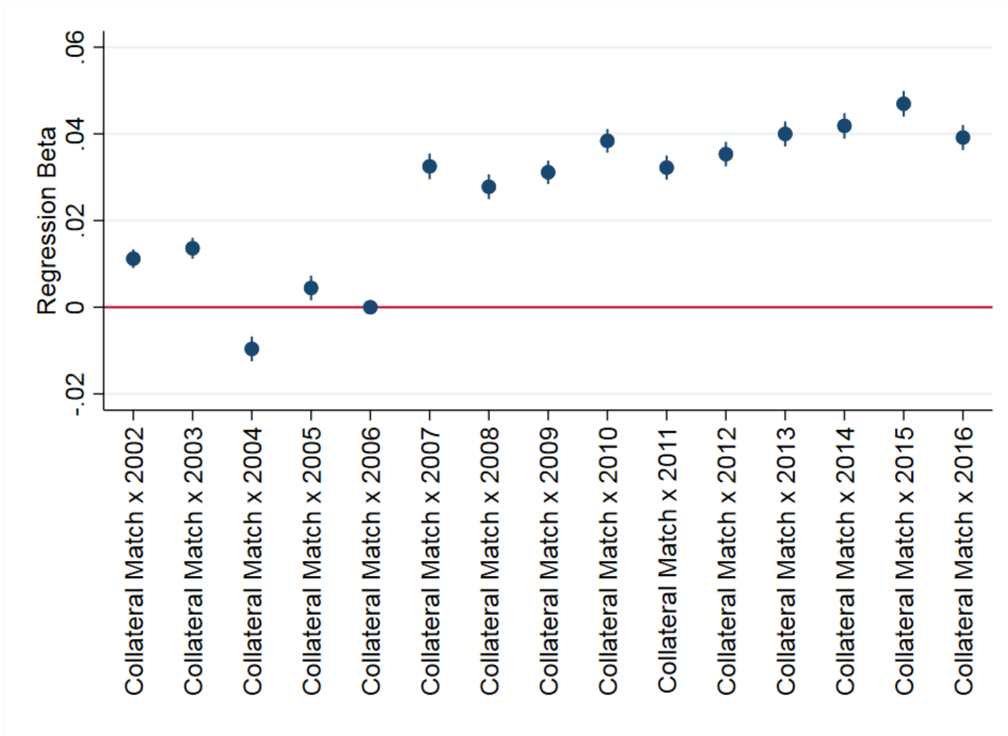


Figure 7: Aggregate Trends - Dynamic Difference-in-Difference

This figure plots the coefficeints from the following regression:

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

based on the sample of loans in Texas between 2002 and 2016. Firm-lender collateral match quality is calculated by comparing the borrower's collateral to lending portfolio of the lender based on all loans in the sample between 2002 and 2016.



7 Tables

Table 1: Summary Statistics

Panel A - Firm Statistics for Baseline Sample

	Mean	SD
Firm Age (2007)	12.73	9.901
Firm Log(Employment) (2007)	2.648	1.513
Repeat Loan (Firm-Lender Level)	0.1976	0.3982
Repeat Loan - Multi-relationship firms (Firm-Lender Level)	0.2074	0.4055
Repeat Loan (Firm-Level)	0.3083	0.4618
New Loan - Total (Firm-Level)	0.6158	0.4864
Fraction - Relationship Lenders	0.1419	0.2642
Fraction - Total	0.5747	0.7127
New Lender	0.5244	0.4994
Average Employment Change (2002-07 to 2008-16)	0.06643	0.6502
Average Scaled Employment	1.098	0.8322
No. of firms	23500	23500

Panel B - Firm-Lender Collateral Match Quality

Percentile	Value
Pseudo 10th pct (mean of 9 - 11)	-0.2531
Pseudo 25th pct (mean of 24 - 26)	-0.1602
Pseudo 75th pct (mean of 74 - 76)	0.1307
Pseudo 90th pct (mean of 89 - 91)	0.2765

Panel C - Firm Collateral Similarity

Percentile	Value
Pseudo 10th pct (mean of 9 - 11)	0.03513
Pseudo 25th pct (mean of 24 - 26)	0.08723
Pseudo 75th pct (mean of 74 - 76)	0.3184
Pseudo 90th pct (mean of 89 - 91)	0.4323

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.

	(1) Loan All	(2) Loan All	(3) Loan All	(4) Loan Multi	(5) Loan Multi	(6) Loan Multi
Firm-Lender Collateral Match	0.084**	0.094***	0.089***	0.103***	0.120***	0.124***
	(0.033)	(0.030)	(0.030)	(0.026)	(0.026)	(0.021)
Observations	38500	38500	38500	23000	23000	23000
County x Industry FE	N	Y	Y	Y	N	N
Firm Controls	N	N	Y	Y	N	N
Firm FE	N	N	N	N	Y	Y
Lender FE	N	N	N	N	N	Y
R^2	0.002	0.076	0.081	0.094	0.387	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

AWAITING CENSUS DISCLOSURE

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	(+)***	(+)***	(+)***
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

Panel B - Inclusion of Lender-Industry Shares

	(1) Loan	(2) Loan	(3) Loan
Firm-Lender Collateral Match	(+)***	(+)***	(+)***
2-digit Industry Share	(+)***		
4-digit Industry Share		(+)***	
6-digit Industry Share			(+)***
Observations	23000	23000	23000
Firm FE	Y	Y	Y
Lender FE	Y	Y	Y

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 Match	(+)***	(+)***	(+)***	(+)***	(+)***
Avg. No of Pre-Crisis Loans		(+)***			(+)***
Lender Share			(+)***		
Time from Last Loan				(-)***	(-)***
Observations	23000	23000	23000	23000	23000
Firm FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y

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	(+)***	(+)***	(+)***
Firm-Lender Collateral Match × Bank	-		
Firm-Lender Collateral Match × Captive Finance		(+)***	
Firm-Lender Collateral Match × Top4			-
Observations	23000	23000	23000
Firm FE	Y	Y	Y
Lender FE	Y	Y	Y

Table 7: 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.

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

AWAITING CENSUS DISCLOSURE

Table 8: 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	(+)***	(+)***	(+)***
Firm-Lender Collateral Match × Industry Performance (3-digit NAICS)	-		
Firm-Lender Collateral Match × Industry Performance (4-digit NAICS)		-	
Firm-Lender Collateral Match × Industry Performance (6-digit NAICS)			-
Observations	23000	23000	23000
Firm FE	Y	Y	Y
Lender FE	Y	Y	Y

Table 9: Aggregate Effects - Counter-factual Exercise

This table presents the aggregate effect on lending under counterfactual firm-lender matching exercises. The includes firms in Texas between 2002 and 2016. Sample is restricted to firms with a loan between 2002 and 2007.

Best Available Match for Collateral	0.1476
90th percentile of Firm-Lender Collateral Match	0.2176
95th percentile of Firm-Lender Collateral Match	0.3134
Maximum of Firm-Lender Collateral Match	0.4267

Table 10: 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 2008-2016 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.

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

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

Panel A - Relationship Lending

	(1) Loan	(2) Loan	(3) Loan	(4) Fraction	(5) Fraction	(6) Fraction
Firm Collateral Match	0.531***	0.499***	0.454***	0.157***	0.142***	0.131***
	(0.020)	(0.020)	(0.020)	(0.009)	(0.010)	(0.010)
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	0.031	0.142	0.166	0.012	0.122	0.136

Table 11: 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 in Column 1-3. In Columns 4-6 dependent variable is average annual number of loans between 2008-16 scaled by the average annual number of loans between 2002 and 2007. 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

	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Fraction	(6) Fraction
Firm Similarity	0.285***	0.295***	0.225***	-0.393***	-0.390***	-0.451***
	(0.021)	(0.022)	(0.022)	(0.036)	(0.038)	(0.039)
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	0.004	0.080	0.099

Panel B - Total Lending

	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Fraction	(6) Fraction
Firm Similarity	0.374***	0.365***	0.301***	\$-\$0.019	\$-\$0.037	\$-\$0.099***
	(0.020)	(0.021)	(0.021)	(0.029)	(0.031)	(0.030)
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	0.014	0.114	0.156	0.000	0.092	0.129

Table 12: 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. 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) $\Delta(Emp)$	(5) $\Delta(Emp)$
New Loan	0.240***	0.243***	0.256***	0.251***	0.272***
	(0.009)	(0.009)	(0.009)	(0.040)	(0.038)
Observations	23500	23500	23500	23500	23500
County x Industry FE	N	Y	Y	N	Y
Firm Controls	N	N	Y	N	Y
Weighted	N	N	N	Y	Y
R^2	0.032	0.115	0.184	0.033	0.358

Panel B - IV

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

	(1) $\Delta(Emp)$	(2) $\Delta(Emp)$	(3) $\Delta(Emp)$	(4) $\Delta(Emp)$	(5) $\Delta(Emp)$
New Loan	0.312***	0.338***	0.212**	1.176***	1.029***
	(0.073)	(0.079)	(0.094)	(0.361)	(0.282)
Observations	23500	23500	23500	23500	23500
County x Industry FE	N	Y	Y	N	Y
Firm Controls	N	N	Y	N	Y
Weighted	N	N	N	Y	Y
First Stage F-stat	358.5	305.7	211.8	22.94	26.14

Table 12: 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.

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

	(1) Scaled Employment	(2) Scaled Employment	(3) Scaled Employment
Similarity x 2001	−0.099	−0.149**	−0.082
	(0.077)	(0.073)	(0.071)
Similarity x 2002	−0.023	−0.056	−0.027
	(0.052)	(0.054)	(0.052)
Similarity x 2003	−0.038	−0.021	−0.020
	(0.053)	(0.050)	(0.046)
Similarity x 2004	−0.003	0.022	−0.009
	(0.057)	(0.047)	(0.056)
Similarity x 2005	0.083**	0.062	0.111**
	(0.039)	(0.038)	(0.044)
Similarity x 2006	0.040	0.004	0.072
	(0.062)	(0.072)	(0.058)
Similarity x 2007	0.052	0.177**	0.107
	(0.087)	(0.075)	(0.089)
Similarity x 2008	0.233**	0.363***	0.318***
	(0.118)	(0.092)	(0.086)
Similarity x 2009	0.358***	0.332***	0.373***
	(0.129)	(0.106)	(0.102)

Continued on next page

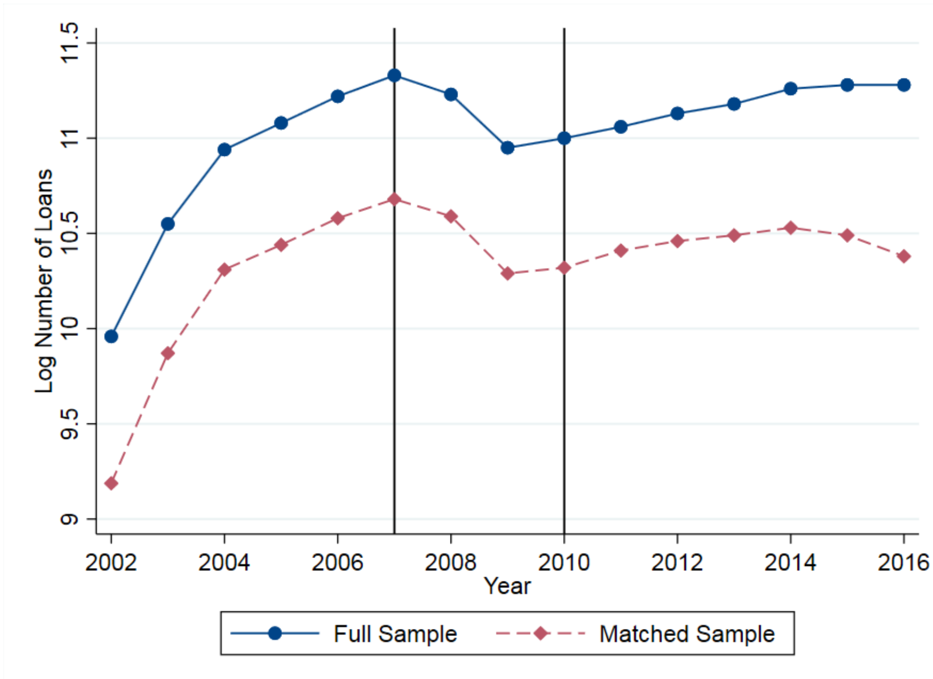
Table 13 – *Continued from previous page*

	(1) Scaled Employment	(2) Scaled Employment	(3) Scaled Employment
Similarity x 2010	0.279**	0.259**	0.209
	(0.134)	(0.125)	(0.128)
Similarity x 2011	0.413***	0.384**	0.404***
	(0.144)	(0.156)	(0.132)
Similarity x 2012	0.411**	0.331**	0.367**
	(0.186)	(0.153)	(0.148)
Similarity x 2013	0.417**	0.179	0.341**
	(0.184)	(0.180)	(0.152)
Similarity x 2014	0.386*	0.309	0.266
	(0.200)	(0.202)	(0.184)
Similarity x 2015	0.326	0.101	0.080
	(0.228)	(0.225)	(0.205)
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 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: 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

Appendix A3 Data Appendix

Figure A2: Sample UCC Filing

[redacted]

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 **829 Graves Street**	CITY **Kernersville**	STATE **NC**	POSTAL CODE **28269**	COUNTRY **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 **344 Main Street**	CITY **Kensington**	STATE **CT**	POSTAL CODE **06037**	COUNTRY **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

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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 A3: 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 annual firm employment in the post-crisis period (2008-16) scaled by the average annual firm employment in the pre-crisis period (2002-07)
Scaled Employment	Firm employment scaled by the average annual firm employment in the pre-crisis period (2002-07)

Table A3: Variable Definitions

Variable Name	Description
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.[31] Hence, reporting incentives may affect the quality of the CRA data when used to measure new credit.

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

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

cards issued to small businesses.[32]

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.[33]

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. 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.

[32] 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

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

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.[34] 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).[35] 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

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

[35] 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.[36]

Table A4 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 A4, I study the extent to which firms are able to substitute to new

[36]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 A5 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 A6 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 A6 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 A4: 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 2008-2016 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

	(1) Loan	(2) Loan	(3) Loan	(4) Fraction	(5) Fraction	(6) Fraction
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

	(1) Loan	(2) Loan	(3) Loan	(4) Fraction	(5) Fraction	(6) Fraction
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 A5: 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 2008-2016 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 A6: Real Assets vs. Blanket Liens - Within-Firm

	(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