How Effective Are Non-Banks in Crises?

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September 2023

Abstract

Banks have been stable lenders in recent years. Yet little is known about non-depository institutions' lending behavior and their effect on business outcomes. Using a novel longitudinal dataset of business loans originated by banks and non-banks, including online lenders, spanning near a decade, I provide new evidence that in contrast to banks, nonbanks and fintech lenders are cyclical lenders in the business loan market. I also show that nonbanks refrain from lending even in the presence of local uncertainty shocks. The cyclicality is not due to demand factors and is exacerbated by both the funding problem of nonbanks and their aversion to uncertainty. The cyclicality is more pronounced for platform lenders, which have more funding problems during crises due to the lack of balance-sheet lending. Nonbanks decrease lending to riskier borrowers more than banks during times of aggregate and regional uncertainty, and most importantly, this cyclicality has a real impact on borrowers of nonbanks. Overall, my analysis demonstrates the volatility of the non-bank lending model in the face of a crisis.

In the last two decades, there has been a substantial transition towards unregulated non-bank lending institutions. Much of the literature on nonbanks revolves around their role in the mortgage market, but little is known about their role in the business loan market and how a more significant presence of non-bank lenders affects the economy. Nonbanks have a special funding structure that is not based on deposit-taking, making

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them susceptible during crises. On the other hand, it is known from the mortgage literature that nonbanks might cater to riskier and underserved segments of the market. Although less is known about the business loan market, there is a perception that this is the case for the SMB loan market, too, and they might fare better during times of crises(Gopal and Schnabl (2022) in the case of financial crisis)[1]. As a result, it is not clear how nonbanks fare during times of uncertainty; whether they have enough funding during crises, and whether they prefer to lend to riskier businesses left behind in times of crises or stay away from risk. All of these have big implications for the stability of the lending market as a whole and health of businesses. Hence, in this research, I analyze how nonbanks lend and substitute for banks, especially during times of crisis, and assess the real implications of this possible cyclicality.

To answer these questions, I use a causal research design to evaluate how non-banks may compensate for the reduced lending when the economy is hit by small and big adverse shocks. The lack of a long longitudinal loan-level dataset is one of the reasons that has prevented the previous literature from employing a causal research design. Many papers have examined how banks cope in the presence of large, aggregate shocks to the banking system in the financial crisis, but little attention has been paid to how nonbanks can interact and fill in the gap in these times. To answer this question, I use a large longitudinal dataset of loans given to businesses in the US. The dataset is ideal for analyzing the roles and competition between different players in this market due to the presence of large and small banks, and nonbanks. The dataset consists of a panel of loans given to millions of businesses in nine years starting from 2014.

I start by analyzing how nonbanks respond to aggregate economic uncertainty. I document that nonbanks significantly reduce their lending during times of high credit spreads, but banks show very weak cyclicality. I also show that this has real consequences: Businesses with past relationship with nonbanks experience lower employment and delinquency in the following years. Given the large stickiness in the market for small

[1]For example, Stanton Chase mentions that "Fintech firms have a level of flexibility that, ultimately, will help them weather this[COVID] crisis. Comparably low fixed overheads and their embracing of advanced technology and artificial intelligence give them a leg up over brick-and-mortar institutions that are not as well-versed in the digital era."

business loans, the previous result can point to the welfare-destructing aspect of the relationship with nonbanks.

In principle, the reduced lending by non-banks during crises could be caused by different supply and demand factors. I first show that the reduced lending is significant, even in the presence of no change in demand by businesses. Specifically, I show in two ways that demand is unlikely to drive the results. First, I show that the results persist even by including the Past Lender Type$\times$ time fixed effect. The fixed effect, also known as Khwaja-Mian regression, removes changes caused by differences in bank and non-bank times varying borrower demand. To cope with unobserved demand changes, I use the merger of banks(and credit unions) as an exogenous shock to bank branch closing to determine the non-bank role when a supply shock occurs in a given market. A merger-induced closing of a branch acts as a supply shock, and, as a result, the cyclicality of non-bank lending in the regions with closed branches is unlikely to be driven by demand factors.

Calculating the impact of branch closings presents a complex challenge due to the inherent endogeneity of the closing decision, which is closely tied to local economic conditions. The decision to close a branch is not made in isolation but is somewhat influenced by the financial health of the region it serves. Banks are more inclined to close branches in unfavorable economic conditions as a strategic response to economic challenges. Consequently, conducting a straightforward regression of credit supply on closing would likely yield a biased estimate of the true impact of these closings on credit availability.

I show that bank mergers are followed by a period in which branches are closed in neighborhoods where the two previously separate buyer and target branch networks are present. The identifying assumption is that the merger is exogenous to economic conditions at the local level in areas where both target and buyer banks have a branch. The loan-level and borrower-level nature of data allows for analysis using Khwaja and Mian (2008) method, which uses borrower $\times$ time fixed effect. This removes possible time-varying borrower-specific characteristics and uncertainty that might contaminate the results.

In principle, borrowers should be able to secure more loans from finance companies during times of uncertainty as they are perceived to have more flexible underwriting practices. On the contrary, I find that during COVID-19 and aggregate credit shocks, nonbank lenders could not fill in the reduced supply gap following the merger-induced closing of a branch. Because the merger-induced closing is unlikely to be caused by demand factors, the analysis using merger shows that the reduced supply exists even in the presence of no demand shocks. The merger experiment also underscores that nonbanks perform well and substitute for small-scale bank supply shocks. This can give us a better understanding of the role of nonbanks and identifying the periods they might be more willing to lend.

While, as shown, the demand is unlikely to present the stark reduced supply, it is vital to understand the channel causing the reduced lending by non-banks. I show that non-banks reduce lending in the presence of heightened risk, even when there is no aggregate adverse shock that might affect nonbank funding. I use abnormally heavy winter snowfall, which affects borrowers in select regions. This experiment is unlikely to affect the supply function of lenders. As a result, differential treatment by banks and non-banks reveals a lot about the differences in the behavior of these two categories and, hence, their supply function. My findings show that, similar to COVID, nonbank companies do not supply many loans during these shocks but are faster regarding their loan offering. Because the local weather shocks are unlikely to be aggregate, this provides evidence of non-banks' aversion to providing loans during times of uncertainty. I also show that lines of credit are used extensively during these events. Finance companies might endogenously not offer credit lines because credit lines allow for potentially large use of credit during times of heightened risk. I show that firms either increase their use of credit lines or turn to term loans for getting funding during these times. On the other hand, I show that firms that turn to banks for term loans mostly do it in later periods. This gives more perspective on the role of nonbanks in the small business lending market: Nonbanks provide smaller and faster loans to businesses that might be in need of money and might restrict lending during times of uncertainty.

The impact of economic shocks on the lending market is one of the key issues in banking. Due to data availability, however, it is unclear whether nonbank companies can help in the event of supply shocks. Following this line, this research attempts to determine whether these lenders can provide stability and support during mild and severe shocks and provide funding when it is needed most. Nonbank lenders differ sharply from banks regarding their business model. As a result of their deposit franchises, banks typically receive large inflows of deposits during times of crisis. Hence, they might be able to lend more than nonbank lenders, whose funding may be harder to come by during a crisis. On the other hand, non-banks might differ in terms of their technology and might be more flexible during difficult times.

My paper is linked to several strands of literature. As a first contribution, I discuss the impact of COVID-19 shock. COVID-19 shock has been well-documented to have had a significant impact on small businesses Bartik et al. (2020), Fairlie (2020), Kalemli-Ozcan et al. (2020). I argue that part of this impact is the decrease in credit supply for firms that rely heavily on nonbank lending. I also contribute to the work on lending to small businesses by online lender companies. Beaumont, Tang, and Vansteenberghe (2022) demonstrate that bank loans can be obtained easily withfintechlending. In line with these, Gopal and Schnabl (2022) demonstrates that the increase in lending by non-banks could reverse the decline in banks' SMB lending after the financial crisis. I add to this literature by introducing the darker side of nonbank companies and also by using causal methodologies to assess the substitution effect between online and other companies. dd to this literature by showing how FinTech lending demand and supply respond to external shocks to banks and the economy. Many papers in the literature use the financial crisis, or later COVID-19, as a source for exogenous shocks to assess how online lending rose to prominence. My contribution to this literature is, first, to analyze the competition between nonbanks and banks using a dataset containing both lenders. And second, using causal methods to quantify the relationship.

To sum up, my work adds to the scant literature on the role of nonbanks in small business lending. This study is one of the few papers assessing the competition between banks and nonbank lenders in one place. While Gopal and Schnabl (2022) documents the emergence of nonbanks following the 2007-2009 financial crisis, this paper analyzes the years after and highlights both the bright and dark side of these lenders. In the next section, I review related literature, and after that, I present my methodologies and results.

1 Literature Review

My paper links to several strands of literature. Several studies explore the impact and value of lending relationships. For example, see James and Wier (1990), Petersen and Rajan (1994), Berger and Udell (1995), Petersen and Rajan (1995) , Blackwell and Winters (1997), Houston and James (2001), Ongena and Smith (2001), Petersen and Rajan (2002), Berger et al. (2005), and Fuss and Vermeulen (2008). In the context of this literature, my research makes a distinctive contribution by shedding light on the intricate interplay between relationship lending and the involvement of non-bank entities. Specifically, I show how companies that have relationships with non-banks differ from banks in terms of their performance during a crisis. This reliance on non-banks can become a potential source of vulnerability when these firms encounter unexpected shocks or financial challenges.

My paper also relates to the literature highlighting the role of banks as liquidity providers. Kashyap, Rajan, and Stein (2002) and Gatev and Strahan (2006) put forward a risk-management rationale to elucidate the distinctive function of banks in facilitating liquidity for households and businesses. Acharya and Mora (2015) demonstrates that during the financial crisis, which revolved around the banking system itself, banks encountered a crisis in their capacity as liquidity providers. Substantial government support made their ability to fulfill this critical role possible. In contrast, amid the COVID-19 pandemic, which had a direct impact on the corporate sector, research by Li, Strahan, and Zhang (2020) and Acharya and Steffen (2020) reveals that the overall deposit inflows proved to be adequate in covering the heightened demand for liquidity resulting from drawdowns. My research adds to this literature by showing whether and when nonbanks provide liquidity. Within the existing literature, my research represents a notable contribution by leveraging comprehensive, granular loan data to delve into the intricacies of the lending landscape, particularly regarding the role played by non-bank entities. I show that non-banks do not act as good liquidity providers during times of crisis or regional uncertainty but provide liquidity during normal times.

My research also links to the research on the effect of COVID-19 on the corporate sector. A recent emerging literature examines how COVID-19 shock affects the corporate sector. Halling, Yu, and Zechner (2020) investigated how U.S. companies accessed public capital markets and discovered that, following the pandemic, notably well-rated firms opted to issue public debt. At the same time, equity issuance experienced a significant decline. Acharya, Byoun, and Xu (2020) reveal that publicly traded companies accumulate cash reserves by tapping into external finance when prevailing capital costs are favorable. This strategy involves seeking a low rate contrasted against anticipated future costs, ensuring a balanced and steady trajectory for overall capital expenses. Notably, while the majority of research concentrates on the corporate sector, there is a relatively limited focus on examining the impacts of the COVID-19 shock, specifically within the banking sector Banks managed to meet the liquidity requirements of businesses by accessing cash inflows from both the Federal Reserve and depositors. Acharya et al. (2020) demonstrate how the collective liquidity demand is factored into banks' stock returns and propose its integration into bank stress tests. Ben-David, Johnson, and Stulz (2021) also documents that a platform of Fintech lenders saw a sudden drop in activity after COVID-19. My unique contribution to this body of research involves an in-depth examination of the actions taken by small private firms, as opposed to public firms, in response to the COVID-19 pandemic and analyzing both banks and nonbanks in the same place. I also show how the finding during COVID extends to other times of aggregate uncertainty: I show that even other times with high aggregate uncertainty, nonbanks reduce lending. Moreover, by using regional shocks, I show that part of the reduction in times of uncertainty is attributable to the uncertainty aversion of nonbanks and partly due to funding problems. The literature on COVID is not able to differentiate between different channels because of the one-off and aggregate nature of COVID. Due to the panel nature of my data and wealth of borrower level information, I'm able to analyze what happens to borrowers of nonbanks years after crisis.

Natural disasters have also been used in studies to obtain exogenous variation in credit conditions. According to Morse (2011), payday lenders serve areas more likely to benefit from natural disasters. Berg and Schrader (2012) uses a disaster- the volcanic eruption in Ecuador- to identify an exogenous increase in loan demand, focusing on how bank relationships enhance credit access following such events. Similarly,Chavaz (2016) shows that lenders with concentrated exposure to markets hit by the massive hurricanes in 2005 increased lending more than banks less concentrated in those areas. Consistent with this result, Cortés (2014) finds that areas with a greater relative presence of local lenders recover faster after disasters. My contribution to this literature is first focusing on business loans rather than personal loans and using detailed firm and loan-level data rather than bank-level datasets and finally being able to analyze the role of nonbanks. I contribute to a growing literature on the effects of natural events on firm decision-making and economic activity (e.g., Giroud, Jindra, and Marek (2012), Bloesch and Gourio (2015), Chen, Lu, and Wang (2017), Dessaint and Matray (2017)). I show that non-banks do not effectively help small firms respond to these unanticipated weather events. In so doing, my work complements evidence, showing that non-banks do not play an important role in mitigating the negative effects of natural disasters (Cortés and Strahan (2017), Koetter, Noth, and Rehbein (2020),Brown, Gustafson, and Ivanov (2021)) . On the other hand, my work shows that non-banks are liquidity provides in the very early days of a local, regional shock. Hence, my work complements the outstanding work by Brown, Gustafson, and Ivanov (2021), who analyze and thoroughly examine how banks provide liquidity in weather events through credit lines in these events. I add value by analyzing the nonbanks' role in these episodes.

Some papers have used mergers as an instrument. In Garmaise and Moskowitz (2006), the effects of mergers on real activity and crime are studied. Many papers have used mergers as an instrument for changes in the concentration of local markets:Hastings and Gilbert (2005) in gasoline markets;Dafny, Duggan, and Ramanarayanan (2012) in health insurance and also relevant to this paper is Garmaise and Moskowitz (2006) and Nguyen (2019), who use a handful of mergers in 2000 to study the effects of merger-induced changes in banks' local market power on real activity and aggregate bank behavior. This paper adopts a similar strategy to study the effect of physical branch closings on local credit supply. Using a disaggregated geographic level and access to past relationships between each borrower and lender allows me to separate the impact of closings from the aggregate market-level effects of a merger, including the competition channel studied by Garmaise and Moskowitz (2006), whereas these effects are potentially confounded by previous work in which exposure is defined as the market level. Also, due to the stickiness of the banking relationship, looking at previous borrowers of a bank rather than total lending of a bank allows for a higher statistical power. With access to loan-level data, I can examine all mergers rather than a few bigger mergers and utilize Khwaja and Mian (2008) regressions to examine borrower switching. Most importantly, I analyze how non-banks act in these events. The data allows me to assess the role of non-bank lenders for a given borrower of a bank by including the universe of lenders.

The research in this paper is also relevant to the broader theoretical and empirical literature on finance and growth (Levine (2005), Clementi and Hopenhayn (2006)). As emphasized in Beck (2009) review, The direction of causality between growth and finance is a standard identification problem, and despite many empirical studies, it remains unclear to what extent financial development contributes to economic growth. Many studies use aggregate country-level data (e.g., King and Levine (1993), Demetriades and Hussein (1996)), which makes inference harder. Measuring financial constraints at the firm level is notoriously difficult; see Hubbard's controversy over the relationship between investment and cash flow (Hubbard (1997)). Most closely related to my paper are recent studies that have advanced this literature by employing firm-level data and innovative identification strategies. Banerjee and Duflo (2014) determines how changes in firm size eligibility for directed credit in India affect firm growth, which is strongly positive. Two studies, Lelarge, Sraer, and Thesmar (2010) and Bach (2014), utilize changes in sectoral eligibility for a French loan guarantee program. The former finds that the program is associated with positive growth effects but also a higher probability of bankruptcy; the latter finds that the program has a positive impact on credit growth and no evidence of substitution between subsidized and unsubsidized finance or an increase in default risk. My paper uses granular supply and demand shocks and firm-level data to assess the role of financing on firms' growth, including employment and sales. My contribution is by showing how lack of access to nonbank funding can have real effects. Employing data from a lender that utilized an automated algorithm during its application assessment process, Fracassi et al. (2016) demonstrates a substantial increase in the likelihood of survival, higher revenue generation, and increased job creation among startups that successfully secure funding. Additionally, Fracassi et al. (2016) underscores the greater significance of loans in terms of survival, especially among subprime business owners with higher levels of education and limited managerial experience. While Fracassi et al. (2016) looks at the cross-section of firms by analyzing firms that missed the funding threshold versus the ones that did not, my study looks at the effect during times of uncertainty and normal times, essentially making a time series analysis. Using LBD and SBA data and banks' share in a given county as IV,Brown and Earle (2017) analyzes linked databases on all SBA loans, lenders, and U.S. employers to estimate the effects of financial access on employment growth. Using interstate banking regulations, LRD data, and RDD around SBA employee eligibility cutoff, Krishnan, Nandy, and Puri (2015) show that firms' TFP increases after their states implement banking deregulations.

Fleckenstein et al. (2020) analysis reveals that the fluctuations in CLO institutions' activities account for the cyclicality observed in the syndicated loan market. When credit conditions tighten for a given borrower within the same loan deal, CLOs exhibit a more pronounced reduction in loan originations and an increase in loan spreads compared to banks. Notably, the cyclicality in CLO lending, rather than the health or capacity of banks, predominantly explains the decline in lending activity during both the Financial Crisis and the COVID-19 pandemic. Additionally, they find that the cyclicality in CLO lending aligns with corresponding fluctuations in flows to CLOs. My contribution is, first, to analyze the business loan market and fintech and other lenders participating in it rather than CLO funds and syndicated loans. Second, my dataset consists of mostly very small firms, and hence, I look mostly at a different sample of firms. Third, the nonbanks in my dataset are different lenders. They are not CLO funds. Rather, they are online lenders, independent finance companies, and financial arms of manufacturers. I also look at the real effects on each borrower. By having access to borrower information and location, I can also assess the causal effect using regional shocks. The syndicated market, due to the presence of bigger firms and also the pooling, is harder to be analyzed using regional shocks.

My study contributes to an emerging literature that tries to understand the role of banks in integrating portions of local credit markets where information frictions limit arm's length transactions (e.g., securitization). By allowing credit to flow between markets, financial integration changes the effects of local credit demand shocks. Ben-David, Palvia, and Spatt (2017) find that deposit rates increase when banks face strong external loan demand. Consistent with this idea, Goldstein, Chakraborty, and MacKinlay (2016) find that local business lending declines when banks reallocate capital toward areas with housing booms, but that this result does not hold for large nationwide lenders. My paper looks at related economic mechanism, in the case of severe weather shocks, using a fully disaggregated approach and a strategy to identify exogenous credit demand shocks. I find that banks can withstand these local shocks, but non-banks do not do best in these circumstances. I also show that banks do not reduce lending in unaffected regions, but nonbanks do reduce lending.

Number of studies analyze the effect of macro and local economic factors on banks' abilities to lend. Levine et al. (2020) shows that new airline routes introduced between banks' headquarters and branches lead to a county-level increase in lending of a given bank. Bord, Ivashina, and Taliaferro (2021) shows that banks affected by the decline in real estate prices during the Great Recession systematically contracted their credit to small firms, negatively impacting county employment. The positive supply of regional unaffected banks partially offset this effect. Using call reports data Acharya, Engle III, and Steffen (2021) provide evidence consistent with a "credit-line drawdown channel" to explain the large and persistent crash of bank stock prices during the COVID-19 pandemic. Stock prices of banks with large ex-ante exposures to undrawn credit lines and large ex-post gross drawdowns declined more, especially of banks with weaker capital buffers. These banks reduced new lending, even after stabilization policies and if deposit inflows accompanied drawdowns. Several studies analyze the effect of banking shocks on borrowers. Using census LDB and Dealscan data, Chodorow-Reich (2014) shows that after the great recession, firms who relied on banks connected to Lehman had more difficulty getting loans and worse future employment outcomes than other firms. Using Dealscan and Compustat bank data, Schwert (2018) shows that firms without a public debt, which they call bank-dependent firms, borrow from well-capitalized banks, while firms with access to the public debt markets borrow from banks with less equity capital. Based on a counterfactual exercise from its empirical matching model, it finds that, in the period surrounding the financial crisis, bank-dependent firms faced 6.6% less loan supply shrinkage from their pre-crisis relationship banks relative to the reverse matching assignment, that is, bank-dependent firms borrowing from low-capital banks. Acharya et al. (2020) reveals that in the period encompassing the downfall of the asset-backed commercial paper (ABCP) market in the final quarter of 2007 and the initial half of 2008, banks with more substantial exposure to ABCP conduits engaged in substantial renegotiations, imposing notably stricter terms on existing credit lines extended to borrowers who had breached covenants. My study adds to this literature by understanding how nonbanks fill in the gap in the presence of these banking supply shocks.

In addition to being consistent with theories arguing that credit lines are a valuable and efficient liquidity management tool (e.g., Shockley and Thakor (1997), Holmström and Tirole (1998)) and that banks are ideal providers of this liquidity (e.g., Kashyap, Rajan, and Stein (2002), Gatev and Strahan (2006)), my findings also contribute to the broader liquidity management literature (e.g., Almeida, Campello, and Weisbach (2004), Denis and Sibilkov (2010), Campello et al. (2011)). As Almeida et al. (2014) discuss, this literature emphasizes the increasing importance of cash holdings as a liquidity management tool, particularly for financially constrained firms that face large aggregate liquidity risks.

By showing that banks provide liquidity insurance to smaller local firms that are susceptible to cash flow shocks but not in a position to manage them with internal funds fully, my findings relate to the large literature on the value of lending relationships, suggesting a specific channel through which banking relationships are valuable.

Other papers on relationship lending draw a bright side view of relationship lending. Drawing on comprehensive data from Dealscan, which consists of loans to bigger firms, some studies build upon the insights provided by Bharath et al. (2011), who demonstrated that repeated borrowing from the same lender yields tangible advantages. Borrowers with established relationships experience benefit from decreased collateral requirements and are more likely to secure larger loan amounts, which underscores the importance of fostering enduring lending relationships and how they can contribute to improved borrowing terms and access to vital financial resources. Through a cross-country meta-analysis, Kysucky and Norden (2016) provides valuable insights into the advantages of robust borrower-lender relationships. However, the research discerns variations in lending outcomes based on distinct dimensions of these relationships. Notably, enduring, exclusive, collaborative bank relationships positively correlate with increased credit availability and reduced loan interest rates. These advantages are more prevalent in the United States and countries with heightened competition among banks. Remarkably, the study discovers that these advantages do not rely on the importance of small and medium-sized enterprises within an economy. This implies that the widespread practice of relationship lending doesn't always result in consistently favorable outcomes for borrowers. I add to this literature by analyzing how bank and nonbank relationship lending differ in terms of outcomes for borrowers.

2 Data and Summary Statistics

This section describes the data sources used for this study, key facts, and summary statistics. All variables are winsorized at 0.1% and 99.9% levels. My primary data source is a large monthly loan-level dataset from one of the credit bureaus. The dataset contains all loans given to millions of businesses from 2014 to 2022. The firms are randomly selected from the universe of all firms, which comprises around 10% of data. Moreover, the dataset contains monthly status, including the total balance of each loan. The dataset contains detailed information on different financial products sold to small businesses, including lines of credit, credit cards, loan terms, and other financial products extended by banks, credit unions, investment companies, fintech companies, and financial arm of manufacturers(Captive Finance). The dataset contains a rich set of business and loan characteristics, including exact business location, name, highest executive name, business age, number of employees, annual sales, business credit score, bankruptcy filings, number of inquiries, and collection counts.

I include data from 2014 through February 2020 for the normal-times analysis. For evaluating the changes brought on by the COVID-19 crisis, I assume that the crisis started in March 2020 and includes all years of 2021 and 2022. As is shown in table 1, the median annual sales is around 459,000, and the median annual sales per employee is 115 thousand dollars. As the summary statistics show, a striking feature of the US small business industry is that most businesses have less than twenty employees. On average, businesses started in 2006, and the median start year is 2009.

A small fraction of businesses have high-risk profiles, delinquency status, or tax liens. A business credit score between 1 and 10 is considered high risk, and a score between 11 and 25 is considered medium-high. A score between 51 and 75 is considered low-medium risk, and a score higher than 76 is considered low risk. With this in mind, more than 5 percent of businesses are considered high-risk. Around 10% are considered medium-high risk, and the majority(55%) are considered medium risk. Around 30% are either low-medium risk or medium risk. Because variables are winsorized at 1% and 99%, most firms do not have any judgments. In the un-winsorized version of the variable, around 20 thousand firms have at least one public judgment. Most firms do not have legal liability, but the average amount (including those who have zero) is 1384. The reason for the relatively large average, although most businesses do not have legal liability, is that the ones with liability owe very large amounts. Businesses with nonzero liability owe $36,000 in liability, and top 90^{th} percentile owe more than \$100,000. Relatedly, most businesses do not have tax liens, but of the businesses that have tax liens, on average, there are 2.95 counts of liens. This points us to the fact that for the businesses that are facing problems, the degree of problem is exponentially worse. This is the case for the number of derogatory filings, although to a lesser extent. Around 95 percent of businesses do not have any derogatory filings. There are, on average, 2.85 derogatory filings for firms with a non-zero number of filings. The same is true for the number of bankruptcy filings. Less than 0.5 percent of businesses (109,000 have at least one bankruptcy filing all of the years) have bankruptcy filing. The same pattern is present for other risk measures: Less than 3 percent of businesses have collections in place. Less than 8 percent of businesses have nonzero days beyond trade (which means any loan or line of credit that has payment overdue). For the ones with nonzero days beyond trade(DBT), the average number of days is equal to 47 days.

Given that the dataset tracks payments and loan-level payment history, many important loan statistics can be deduced. A business's average dollar balance across all trades is equal to 14,871. This number equals 47,444 for term loans, 31,226 for lines of credit, and 4,829 for credit cards, and on average, there are 4.8 UCC counts. Table 2 provides summary statistics using the trade dataset. Total utilization is around one-third. The loan term is equal to 8 years on average. The balance per original loan amount for term loans is equal to around 60%, and for lines of credit is equal to around 50%. The bottom panel shows that the term loan market is split between depository and non-depository institutions. However, the credit card market is mostly supplied by depository institutions. As is evident in tables 3-6, credit usage and other loan characteristics are different for different types of institutions. Banks tend to give loans with higher amounts. On the other hand, the loan term is more or less similar for fintech and banks but is significantly shorter for manufacturers. Finance companies tend to offer lines of credit with the highest amount and manufacturers with the lowest amount. Online lenders mostly do not offer any lines of credit.

I also make use of and append a variety of other datasets. Data on merger activity and branch closings are from the FDIC BankFind Suite Events & Changes. I use FDIC's Summary of Deposits(SOD), which provides branch location and other characteristics of FDIC-insured institutions. This data links each branch to its parent bank and provides other branch-level information, including deposits, street address, and branch's latitude and longitude. I use data from 2014–2022 and map branch locations to their census tract using Census Tiger Files and later using USPS zipcode crosswalk files to zipcodes[2]. Some branches are dropped because their latitude and longitude data are missing, and their recorded street address is either invalid or incomplete.

I also use Census ACS to get yearly demographics information from 2014-2022, which is used for controlling for time-varying regional characteristics, including population, percentage of Hispanic or African-American, percentage of single, percentage employed, percentage college educated, and per capita income.

Nonbank lenders are a large class of heterogeneous investors. They all lack the deposit-taking feature of banks. Banks compete with these lenders in lending markets but do not issue deposits. Finance companies do not have deposits or benefit from deposit insurance, and as a result, capital regulations do not apply to them. They are, however, subject to the same regulations as banks at the federal and state levels, such as usury limits. Many businesses instead seek debt financing from a variety of sources. Depository institutions like banks, savings associations, and credit unions, as well as online lenders, commercial finance companies, specialized lenders, nonprofits, and a wide range of government and government-sponsored enterprises, are among the providers. Historically, businesses sought credit from banks; however, as banks have merged and consolidated, particularly after the Great Recession, they have provided less financing. From 1990 to 2022, the number of banks decreased by 12 percent. While many counties gained or retained bank branches between 2014 and 2022, the majority lost branches.

"Nonbank" refers to a variety of lenders and lending models that differ in structure, market focus, and financing activities. Finance companies, also known as asset-based lenders, are the largest. Leasing companies provide equipment or vehicles to small busi-

[2]using geopandas

nesses. Moreover, online lenders, or fintechs, are the newest players in the industry and operate in a variety of ways. There are many other finance companies and asset-based lenders among the largest nonbanks, two of which are captive finance companies and independent finance companies. A captive finance company is owned by a manufacturer and lends almost exclusively against its products. An independent finance company is not owned by a bank or a manufacturer and lends more widely than a bank or a manufacturer.

3 Aggregate Shocks: Nonbank Behaviour in the time series

There has been a shift toward unregulated nonbank lenders in the US and abroad over the past 20 years, raising concerns about increased financial fragility. It is therefore, essential to analyze how nonbank lending might evolve. Throughout this section, I demonstrate that nonbank lending is correlated with aggregate economic conditions. The nonbank's share of total lending is highly associated with aggregate credit conditions, as measured by credit spread, defined as the difference between below investment grade (below BB) yields and ICE BofA US High Yield Index Option-Adjusted Spreads.

Option-Adjusted Spreads (OASs) are calculated spreads between a computed OAS index of all bonds in a given rating category and a spot Treasury curve. Market capitalization is used to weight each constituent bond's OAS in an OAS index. In ICE BofA High Yield Master II OAS, bonds rated below investment grade (BB or below) are used as an index. The ICE BofA US High Yield Index value tracks the performance of US dollar denominated below investment grade rated corporate bonds issued in the US domestic market. Securities must have a below investment grade rating (based on an average of Moody's, S&P, and Fitch) to qualify for inclusion in the index, as well as a country of risk that is rated as investment grade (based on an average of Moody's, S&P, and Fitch long-term sovereign debt ratings). The security must have over one year of remaining maturity, a fixed coupon schedule, and a minimum outstanding amount of $100 million. Indexes include zero coupon bonds, global securities (debt issued simultaneously in the eurobond and domestic bond markets), 144a securities, and pay-in-kind securities, including toggle notes. To qualify, the callable perpetual securities must be at least one year old from the first call date. If they are callable within the fixed rate period, fixed-to-floating rate securities also qualify. The Index excludes securities that are DRD-eligible and defaulted.

Capitalization-weighted index constituents are based on their current outstanding amounts. Amounts accrued interest are calculated assuming next-day settlement except for U.S. mortgage pass-throughs and U.S. structured products (ABS, CMBS, and CMOs). U.S. mortgage pass-throughs and U.S. structured products are calculated assuming same-day settlement. Cash flows received from bond payments during the month are retained in the index until the end of the month as part of the rebalancing process. Cash does not earn reinvestment income in the index. On the last calendar day of the month, the index is rebalanced based on information available up to and including the third business day before the last business day. The Index includes issues that meet the qualifying criteria for the following month. At the next month-end rebalancing, issues that no longer meet the criteria are removed from the index.

Figure 14 shows the monthly credit spread time series. As a result of COVID-19, there was a significant spike in the spread. Additionally, there are smaller spikes throughout the sample, including a small spike in 2018. A combination of factors led to significantly widening credit spreads in 2015 and 2016. There was an increase in investor risk aversion due to global economic concerns, particularly in regions like Europe and China. Credit spreads widened as a result of the substantial drop in commodity prices, particularly in the oil sector. Credit spreads increased as investors became more risk-averse due to increased market volatility. Corporations had to pay more to borrow money. Geopolitical events like conflicts, political instability, and financial crises like the Greek debt crisis impacted credit spreads. Higher credit spreads also resulted from weak corporate earnings and concerns about companies' ability to meet debt obligations, particularly for lower-rated companies. As a result of reduced market liquidity, investors demanded higher yields to compensate for illiquidity risks. In 2015, these factors, in various combinations, impacted credit spreads differently across sectors, credit ratings, and specific contexts, making it necessary to analyze the financial and economic landscape to understand why credit spreads were elevated. Figure 14 demonstrates that total nonbank lending is highly negatively correlated with high yield spread. In times of high uncertainty and as can be seen nonbanks are less likely to fund businesses when needed.

I then turn to loan-level analysis and examine how the credit spread affects different loan features. Using micro-level regression also allows for the use of different fixed effects and time-varying borrower characteristics. Specifically, the following regression is used:

$$Y_{i,a,t,g} = \sum_{s\, \in \mathcal{G}} \alpha_s 1\{g{=}s\} \times \text{Credit Cycle} + \text{FEs} + \beta \text{Region Chars}_{t-12} + \theta \text{Borrower Chars}_{t-12} + \varepsilon_{i,a,t,g} \tag{1}$$

Where g is lender type, a is the zip code containing the business, t is the month, and i denotes the business. Credit cycle is the scaled credit spread measure such that the minimum and maximum are equal to -1 and 1. The results are shown in table 14 using various fixed effects. I find that bank lending is weakly cyclical, but nonbank lending, especially lending by online lenders, is very cyclical. Also, the average amount of loans given and the APR have the same cyclicality. The results indicate that nonbank finance companies are highly cyclical. In contrast, nonfinance companies and banks show weak cyclicality.

Knowing the determinants of this cyclicality is of high importance. First, it helps in the case of policy intervention. If the funding is causing cyclicality, there can be a case for targeting and regulating the funding source of nonbanks, including requiring more capital buffers. On the other hand, if the cyclicality is caused by reluctance to lend during uncertain times, even when there are no funding problems, then it will be harder to regulate the lending, and most importantly, the regulation method will be different. The regulation should either incentivize lending by providing more loan guarantees during downturns or supplying loans separately using alternative sources.

One of the methods in understanding the determinants of the cyclicality channel is by analyzing lenders' responses with different funding structures. In table 16, I analyze the cyclicality of lending of firms grouped by whether the lender is a platform lender or not. I use the following regression

$$Y_{a,t,g} = \beta_s 1\{\text{Platform Non Bank}\} \times \text{Credit Cycle} + \text{FEs} + \beta \text{Region Chars}_{t-12} + \varepsilon_{a,t,g} \quad (2)$$

to analyze the issue. The regression is run at the zip-code level. a denotes zip code, t is month, and g denotes the type of lender: bank, nonbank platform lender, and other nonbanks. Hence, each observation denotes the total lending of a given lender type in each zip code and month. The platform dummy allows for analyzing how much the loan probability and other loan characteristics of the platform and non-platform lenders differ during times of uncertainty. Table 16 provides evidence of a possible channel behind the cyclicality. As is evident in table 16, platform nonbanks refrain from lending in times of high uncertainty much more than other types of nonbanks. Platform lenders are more cyclical than other non-bank lenders. This shows that part of the reason behind this cyclicality comes from the funding channel. The platform lenders connect investors and borrowers. Hence, in the event of a crisis, the investors are less likely to lend in these situations, and hence, borrowers of platform lenders will have a harder time finding investors in these platforms. The results show that bank-owned nonbanks are much less cyclical, pointing to the fact that the funding source is one of the reasons behind the cyclicality. The main difference between platforms and other types of lenders is the funding structure: platform and partnership lenders connect borrowers and lenders in the loan market. These lenders will have more difficulty during times of crisis because they have to get funding in real-time. On the other hand, other types of lenders have access to funds acquired via different channels, which will give them some buffer in this regard. The results point to the funding channel as one of the factors driving the cyclicality. Hence, this channel might be one of the reasons nonbanks significantly less during a crisis. Table 15 confirms that previous borrowers of nonbanks have a much lower probability of borrowing during adverse credit cycles, loan slightly lower amounts, and pay significantly higher interest rates. Future employment and sales of these borrowers are also significantly lower. As can be seen, the delinquency rate of these businesses is higher, and the borrowers tend to change their lenders more frequently as well during these credit cycles. The aggregate evidence points to possible supply and demand channels regarding non-bank lending. In the next sections, I dissect these channels using different regional-level instruments.

4 Supply Channel: Merger of Depository Institutions

The previous sections highlighted how nonbanks behave in the presence of aggregate shocks. I showed that nonbanks' lending decreases in the presence of adverse credit shocks. In this section, I use the merger of financial institutions and a region's exposure to the merger to evaluate the potential role of non-bank entities in providing assistance during supply shocks. Mergers of financial institutions can give a plausibly exogenous shock to branch closing if the target and acquired branches are relatively close. In this section, I analyze the effect of merger-induced bank closings on credit supply by banks and non-banks. The main regression of interest is

$$\begin{aligned} Y_{i,b,a,t,g} = &\sum_{s\,\in\mathcal{G}} \alpha_s \text{Closed}_{b,t,a} \times 1\{g{=}s\} + \text{FEs} \\ &+ \beta \text{Region Chars}_{t-12} + \theta \text{Borrower Chars}_{t-12} + \varepsilon_{i,b,a,t,g} \end{aligned} \tag{3}$$

where g is lender type and $\mathcal{G} = \{\text{Same Lender,Other banks,Nonbanks}\}$ is the set of lender types. All regressions in this paper are clustered at the zipcode level. The regression is run at the monthly level. Closed indicates whether a given branch is closed or not. i indicates a given firm, b indicates bank, t is year-month, τ indicates horizon (in months) and a denotes the region (zipcode). Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. In some settings, I also add Borrower$\times$Time fixed effect, which turns the regression into Khwaja and Mian (2008) regression. As explained before, this removes the change in lending by banks and nonbanks due to changes in demand by certain types of borrowers. Y is different loan characteristics: The number of loans taken from a given bank, loan amount, credit limit, loan APR, Credit balance change for an existing credit line, and change in the line of credit usage. I also analyze the heterogenous effect by analyzing of businesses with prior relationships with a bank for smaller firms, COVID, and credit spread.

The pure OLS estimation leads to bias because ε and the variable Closed variables are correlated. The reason is that the decision to close a branch is potentially correlated with the region's economic conditions. I use the exposure to mergers as an IV for branch closing. I define exposure of a given depository institution to a merger if both buyer and target have branches in a given region. Hence, the following first-stage regression is used for the IV approach:

$$\text{Closed}_{b,a,t+\tau} = \gamma \text{Exposure}_{b,t,a} + \text{FEs} + \text{Controls} + \nu_{i,b,a,t+\tau} \tag{4}$$

Where t denotes month, Close denotes whether a branch is closed or not. Exposure is equal to one if a zip code has branches from the target and the acquirer. Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The fundamental identifying assumption is that future loan changes are exogenous to the exposure to the merger of banks. This means whether a firm borrows more in the future is orthogonal to whether the branch is exposed to a merger. One important observation is that the final decision to close can be endogenous, but this does not undermine the exogeneity of the instrument. Table 8 and figure and figure 5 presents the point estimates corresponding to equation (4) . As can be seen, the exposure to merger results, on average, a 20% higher closing rate after a year. The effect almost stabilizes after a year, meaning the merger leads to closing by a lag of around one year. Overall, table 8 depicts a clear picture of the effect of branch location on the probability of closing in the case of mergers.

Table 9 presents the base results regarding lending for borrower-lenders that had a previous relationship, following a possible closing for the sample of firms that had a prior relationship with a bank compared to lender-borrower pairs where the lender did not close the branch. I combine target and acquirer banks lending before and after the merger. Loan Num denotes the cumulative number of loans given relative to the number of loans in the incidence of the merger. Hence, Loan Num denotes the number of loans from the merger to 12 months later. Loan Amount, APR, and Limit are the loan amount, APR, and limit for loans taken in the past twelve months. As explained before, The regressions are instrumented by the 12-month lag of the Exposure variable. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. I set the exposure equal to one if both the target and acquirer have at least one branch in the zip code and the date is either equal to the merger date or after that.

The results show that after the closing, the firms have less probability of getting a loan from the same lender, and the amount borrowed conditional on getting a loan from the bank is lowered. The interest rates on loans also see an increase. The result points us to the fact that branch closing hurts relationships between a firm and its main lender. The closing can have a negative shock on relationships: A business might have a tie to a branch or a loan officer, and when the branch closes, the business might not prefer, or might not be able to, get a loan from another branch and hence have to borrow from another lender. The results indicate that the reduced supply is partially countered by the increase in supply by other lenders. This shows that other lenders might fill in the gap of the lost loan supply. As seen in table 9, much of this reduced supply is filled by non-banks. This means that non-banks fill in the gap of business lending, at least in the short term. The loan amounts are lower compared to the control group. The interest rates are higher as well. The limit for credit lines is also lower relative to the control group. As can be seen in table 20, the effect on other types of products, including commercial credit cards, is not statistically significant. This is reasonable as these are not purely financial products. As expected, closing leads to a higher number of inquiries as firms might have to inquire from multiple lenders both to get lower interest rates and also because some loan applications might be rejected. Table 21 shows the results for the net lending from all top 20 lenders in a given zip code and for borrower-lender firms with no relationship. It can be seen there is almost no effect on total lending by the lender to a given borrower. This confirms that the main effect of closing is through the adverse effect on the relationship.

Table 10 shows that the reduced overall borrowing cancels out to a large extent when the borrower has at least two relationships . The interesting fact is that borrowers reduce their borrowing from the lender with closed branches even to a larger extent relative to the previous case. This happens because the business increases its borrowing from its other active lenders. This is apparent as the loan increase by other lenders has the same magnitude as the amount of decrease in loans by the previous lender.

To investigate how the impact of closings varies by business cycles, I estimate the equation for COVID and credit cycles. The results are shown in table 13 and 12. As is evident, non-banks did not fill in the gap of SMB lending following a merger during COVID and, in general, helped less during credit spread shocks. This brings in the concept of the volatility of non-bank companies during crises due to their funding issues and possible risk aversion. An important fact about the analysis is that because the instrumented merger-induced closing of financial institutions are not because of demand, the cyclicality of this substitution is less likely to be caused by demand factors. The lack of lending during the times of high spread but not COVID-19, points to the fact that the reduced supply is either because of risk-averse behavior of non-banks or funding problems unrelated to investor income channel effect. During crises, investors are averse to lending due to uncertainty but they also might have less propensity to invest due to income shocks as well. The 2016 higher credit spread shocks underscore the fact that the effect is present even in the presence of no income shocks. As is evident in table **??** the effect of bank closing due to merger-induced local supply shock varies over the years. The effect diminishes over time but is most evident during COVID, where physical presence has been less of an issue. Banks' total lending count is barely cyclical but nonbanks have very cyclical substitution with banks. The same holds for total lending as well. Nonbanks also raise APR significantly more during credit cycles.

Current regulations target branch closings that could result in banking voids. However, what's critical to understand is that this focus on convenience and accessibility overlooks the significance of relationship-building in the banking sector, setting it apart from other industries. The shuttering of branches can profoundly impact credit availability in dense areas, as it might end a longstanding borrower-lender connection that is challenging to replicate.

Firm attributes also influence the value of lending relationships. I further delve into the impact on smaller businesses, specifically those under 5 employees who maintained a relationship. The findings are in table 11. The findings indicate a marginal influence on subsequent employment and sales figures. The results show that there is a heterogeneous effect of closings on firms of different sizes. These results are of importance for several reasons: First, very small businesses are the majority of American businesses. Second, the reduced lending seems to be partially due to less lending by nonbanks. As documented earlier, non-banks might be averse to lending to smaller and riskier businesses. Because of that, nonbanks might not be filling in the gap partly due to lender-borrower mismatch.

Before delving into potential underlying factors, I study the varied pathways through which mergers might influence lending. One theory suggests that lending decreases due to the competition effect. Specifically, lending rates might rise as competitors decrease, leading to a decline in borrowing. This theory is underscored in Garmaise and Moskowitz (2006), where the observed effects diminish when new banks emerge around three years post-merger.

Even though technology has revolutionized the banking and non-banking sectors in the US, local branches remain crucial to obtaining credit and loans—several factors support distance's continued relevance. The primary reason is the inconvenience of borrowers' travel expenses; if the closest branch closes, many might not be able or willing to commute. Geographic proximity is important, but borrowers do not view all nearby branches equally. It is often the result of the unique relationships formed with specific branches that create this distinction. It becomes increasingly difficult for borrowers to seamlessly transition to another lending institution when these relationships are disrupted. According to this perspective, branch closings significantly impact borrowers who rely heavily on information. During the period following the merger, small business lending declined noticeably. Accordingly, branch closings disrupt market lending relationships, which take time to reestablish after they have been ruptured.

5 Why Do Nonbanks Lend Less During Times of Uncertainty? Analysis Using Local Weather Events

The previous sections analyzed the substitution between banks and non-banks using supply shocks. In this section, I analyze the weather demand shocks, which have various advantages. While the aggregate cyclicality and merger results underscore the role of supply in the presence of shocks, it is of importance to determine why this occurs by understanding the lending behavior of nonbanks in the presence of local adverse shocks that do not affect the economy as a whole and is not caused by lender supply or funding problems. These shocks are idiosyncratic but are more extreme in nature as they affect all firms in a given region. Moreover, weather's exogenous nature can help avoid confounding the instrument with other time-varying conditions. Lastly, this event provides a pure setting for analyzing liquidity shock on the local level without the need to use aggregate economy-wide changes. This section uses the abnormal snow cover as an IV for shocks to demand and uncertainty in a region. Due to their severe nature, it allows me to assess how non-banks respond to extreme shocks. I show that during severe weather events, non-bank lenders provide fewer loans than banks, but they offer loans faster.

In addition, I examine whether firms increase their term loan and credit line usage and obtain more loans in response to weather shocks and whether lenders raise interest rates to compensate for the possible riskier lending. Hence, this section examines term loan demand and credit line usage when firms face external liquidity shocks unrelated to their fundamentals.

During severe winter snowfalls, the local supply chain is disrupted, and business operating costs increase As a result of abnormally heavy snowfall, all firms experience liquidity shocks, increasing credit lines' use. The credit line obligates banks to provide financing to firms when they experience negative shocks(Holmström and Tirole (1998)). As mentioned before, I can isolate a pure demand and risk shock arising from these specific local conditions by focusing on weather-induced shocks and avoiding confounding variables.

As mentioned, this section examines how non-bank entities provide liquidity during financial shocks. In spite of the fact that non-banks rarely offer lines of credit, their effectiveness is limited, especially for viable, small-scale borrowers. During times of heightened risk, bank credit lines are an important tool for managing the non-fundamental component of sales volatility and a significant alternative to term loans for solvent smaller firms. As expected, I also demonstrate that lines of credit are heavily used during periods of abnormal snowfall. Online lenders do not provide sufficient funding during severe weather episodes because of a lack of offering of lines of credit and also their reduced lending in times of uncertainty. Several theories show that credit lines might be offered as a monitoring tool by banks(Acharya et al. (2014)), and banks restrict access to credit lines during periods of declining profitability of firms, precisely when firms are in need of funding (Sufi (2009)).

I introduce the vaiable Abnormal Snow as a dummy, which is equal to one if the amount of snow cover is in the 95% percentile in the history of winters in that zipcode (starting from 1950) in a given month. Winter is defined as the three months including December,January and Feburary. Specifically, I use the equation

$$Y_{i,b,a,t} = \alpha \text{Abnormal Snow}_{t,a} \times \text{Lender Type} + \text{FEs} + \text{Controls} + \varepsilon_{i,b,a,t+\tau} \tag{5}$$

where i denotes firm, b denotes bank,a denotes census ZIP Code Tabulation Areas, which I call just zip code, and t denotes time. The snow cover is calculated as follows: For each day, the average snow cover is obtained from the National Oceanic and Atmospheric Administration(NOAA). I consider all stations in the county that the zip code is part of (or has an intersection with) and then average over the stations' values. Each station is assigned a weight proportional to the inverse of its distance. I truncate the nearest distance to be greater than a quarter of the next distance (including stations with distance equal to zero). I use the nearest station value for zip codes with no station in the county.

I then take an average over days in a period to come up with the snow cover measure. The region chars contain different time-varying characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. A borrower's age, number of employees, annual sales, credit score, and bankruptcy filings can change over time.

Table 17 shows the results for the abnormal snow cover experiment. As can be seen non-banks provide less funding than banks, but their lending is made mainly in the first period. Non-bank lenders also increase their interest lending more than bank lenders. Finally, as can be seen, the utilization of credit lines increases significantly more, pointing to the fact that borrowers use credit lines as a liquidity management tool. Non-banks stay away from these products, which fits into the uncertainty aversion agenda: Lines of credit are used in times of high uncertainty. As a result, they might not be favorable to lenders who are less willing to lend in times of crisis. Online lender's quick response comes to how these lenders fit into the overall lending scene. As evident in table 7, non-bank lenders are more transient. The borrowers who switch from banks to non-banks are much more likely to switch back to their initial lender again relative to previous borrowers who switch from non-banks to banks. This fits the narrative that non-banks have expertise in providing quick loans and can offer smaller loans when borrowers cannot find loans elsewhere quickly. This narrative is also confirmed by the nonbanks' quick response to the weather shock.

I identify the important role of non-banks and banks in lending to small firms to deal with these unanticipated weather events. Literature on the effects of natural disasters on firm decision-making and economic activity has grown in recent years(Brown, Gustafson, and Ivanov (2021), Chen, Lu, and Wang (2017),Giroud, Jindra, and Marek (2012),Bloesch and Gourio (2015)). I add to this literature and Brown, Gustafson, and Ivanov (2021) by showing that non-banks lend significantly less than banks during these times. I also investigate whether firms respond to these shocks by drawing on and increasing the size of their credit lines and whether banks charge borrowers for this liquidity via increased interest rates The utilization rate is also much higher during times of uncertainty. As a result of this section, I conclude that non-banks are not as helpful as banks regarding the total amount of loans offered during severe weather shocks, which would cause a significant strain on the local lending market. On the other hand, they are beneficial in the first period when the shocks occur. As a result, a combination of banks and non-banks may be optimal for the small-business loan market, which caters to different needs. Still, the presence of non-banks might have some welfare-destructing aspects due to their volatile nature. As a result, a regulation that limits and monitors non-bank lending might be welfare-enhancing.

6 Conclusion

In this paper, I analyzed the role of non-banks in the market for SMB loans. Using monthly data of loans to millions of firms spanning 9 years, I analyze how non-banks and banks compete in the market for small business loans during different times. I show that non-banks fill the business lending gap, especially for smaller shocks during normal times. On the other hand, I show the darker side of non-banks, where they cannot provide funding during a crisis due to funding issues and lack of offering of lines of credit. On the other hand, I show that nonbanks are good in terms of their speed, and borrowers turn to nonbanks as a short-term solution when a shock occurs. I show that the merger-induced closing of a bank reduces the likelihood of getting a loan from the same bank in a given year, but non-banks make up a significant portion of the lost lending. On the other hand, this supportive effect is non-existent during the COVID crisis and is reduced during credit cycle shocks proxied by credit spread. I analyze how these effects differ on the spectrum of firms and relationships. I find that the merger-induced supply effect gets canceled out for firms with a relationship with another lender. I also show that the employment effect of reduced supply is amplified for very small firms. My analysis demonstrates the volatility of the non-bank lending model in the face of a crisis, different from what happened in the financial crisis, as documented in previous literature.

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7 Figures

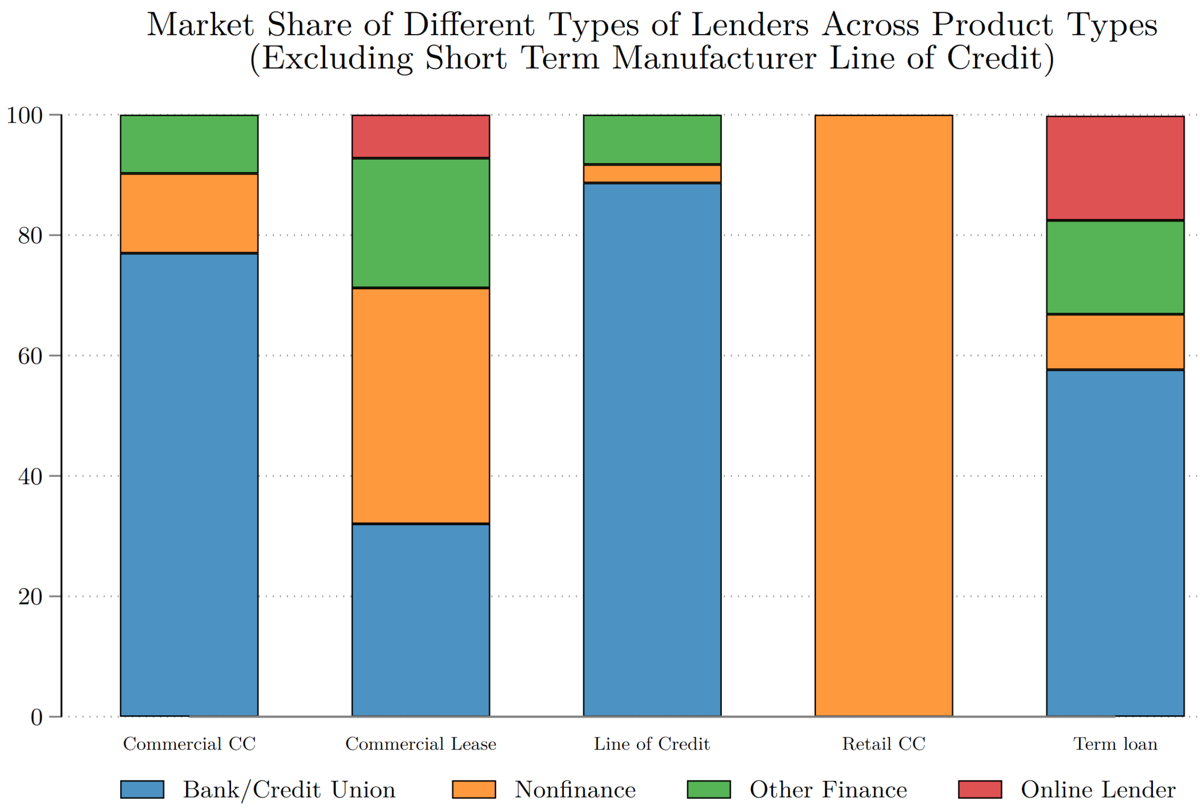

Figure 1: This figure provides market share of different types of lenders in different financial product markets. One of the credit bureaus provides the variables and data used in the analysis for small businesses. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. Bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

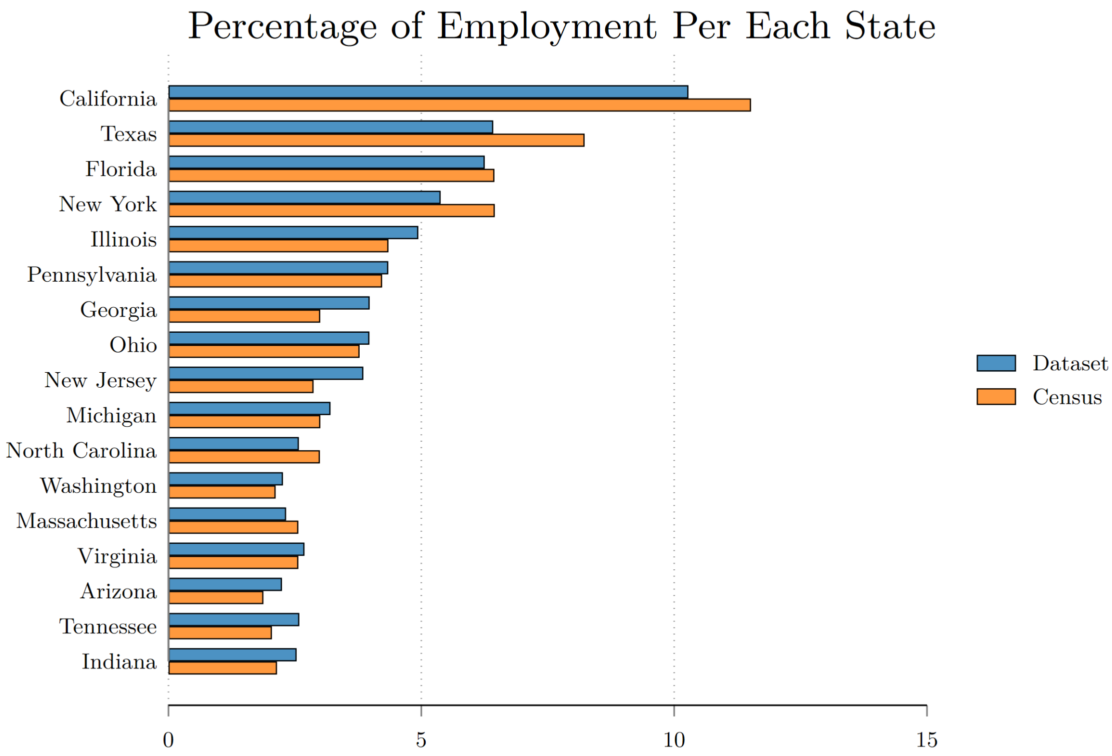

Figure 2: This figure provides a share of each state's number of establishments as the overall number of US establishments. The orange bars use Census data, and the blue lines are the author's calculations using the provided dataset. One of the credit bureaus provides the variables and data used in the analysis for small businesses. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. Bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

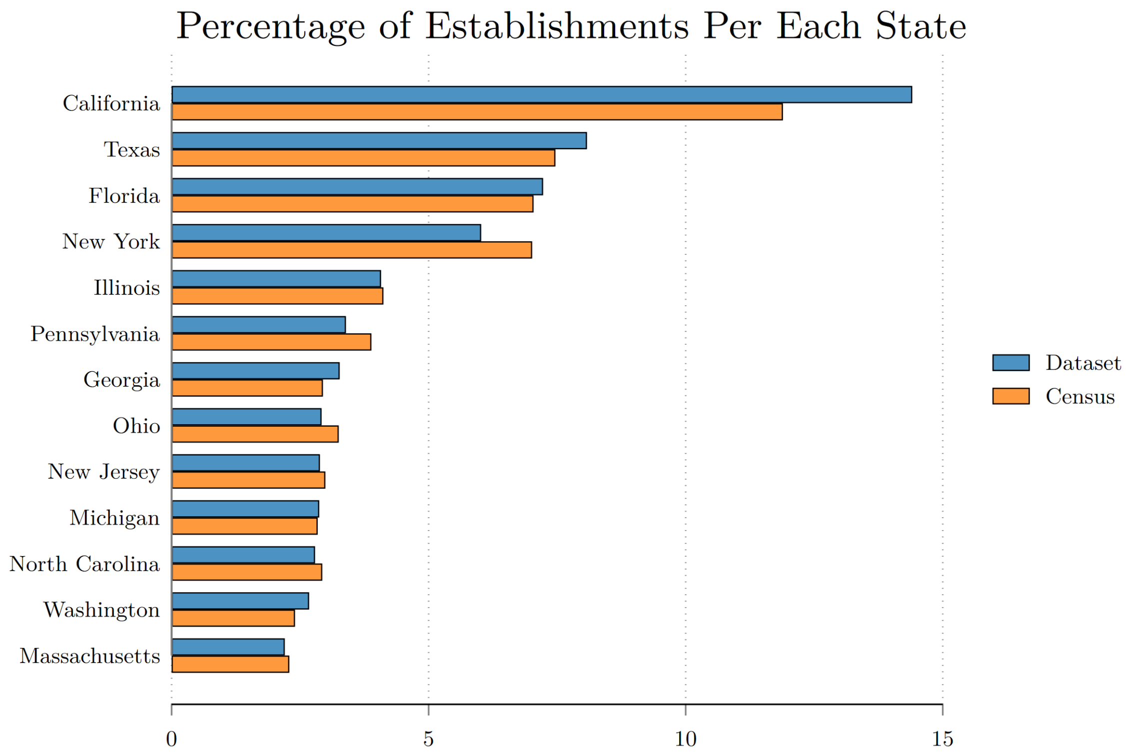

Figure 3: This figure provides a share of each state's number of establishments as the overall number of US establishments. The orange bars use Census data, and the blue lines are the author's calculations using the provided dataset. One of the credit bureaus provides the variables and data used in the analysis for small businesses. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. Bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

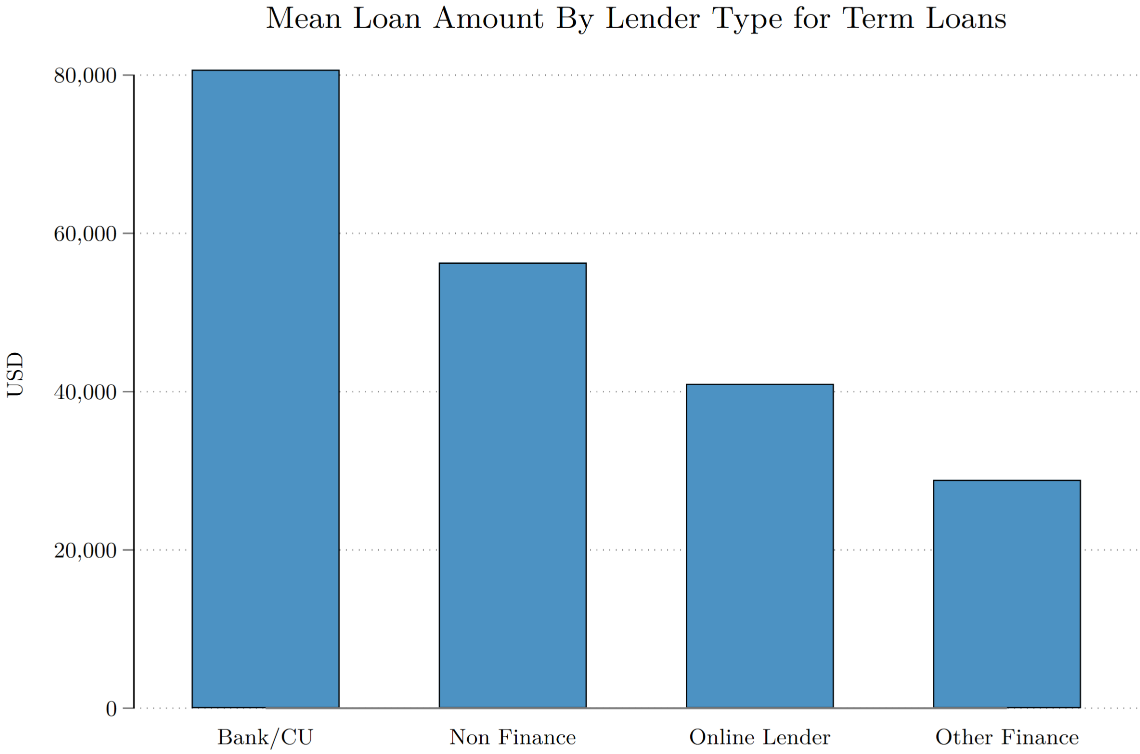

Figure 4: This figure depicts the average loan amount for different lender types in the term loan market. One of the credit bureaus provides the data which covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. Bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

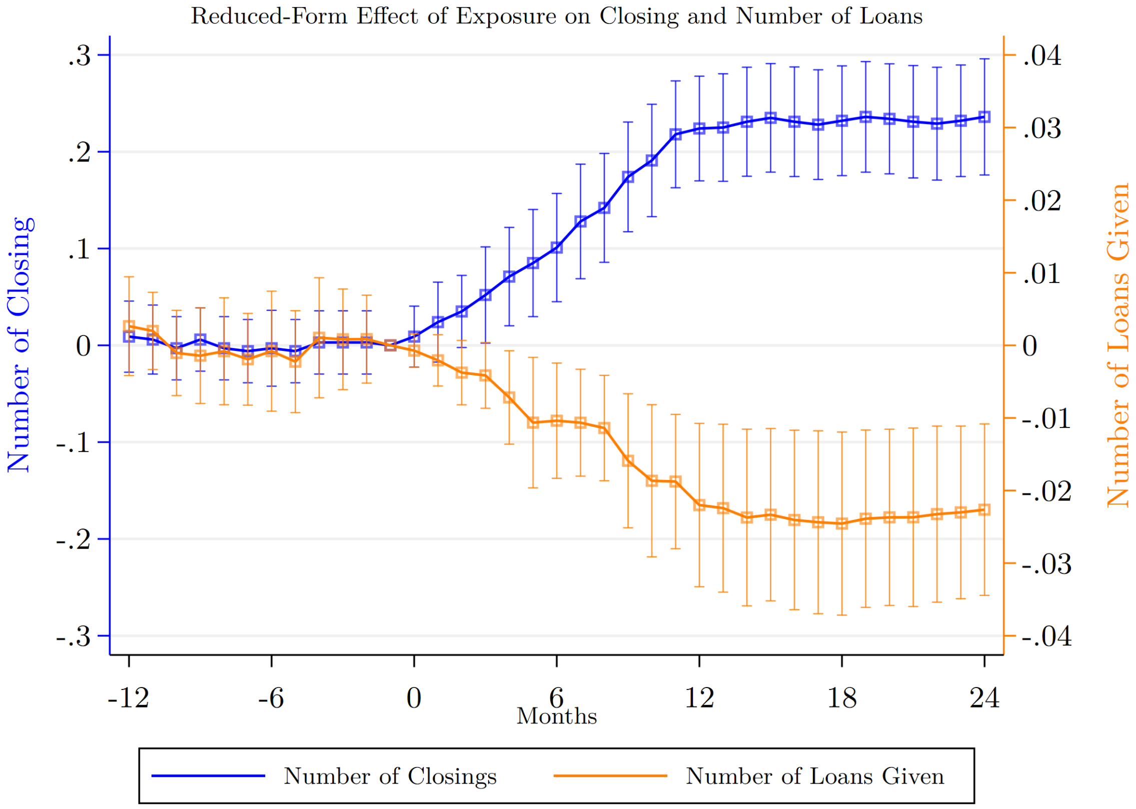

Figure 5: This figure provides a reduced form analysis of cumulative closing and loans given for exposed versus nonexposed groups after a merger. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. Bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

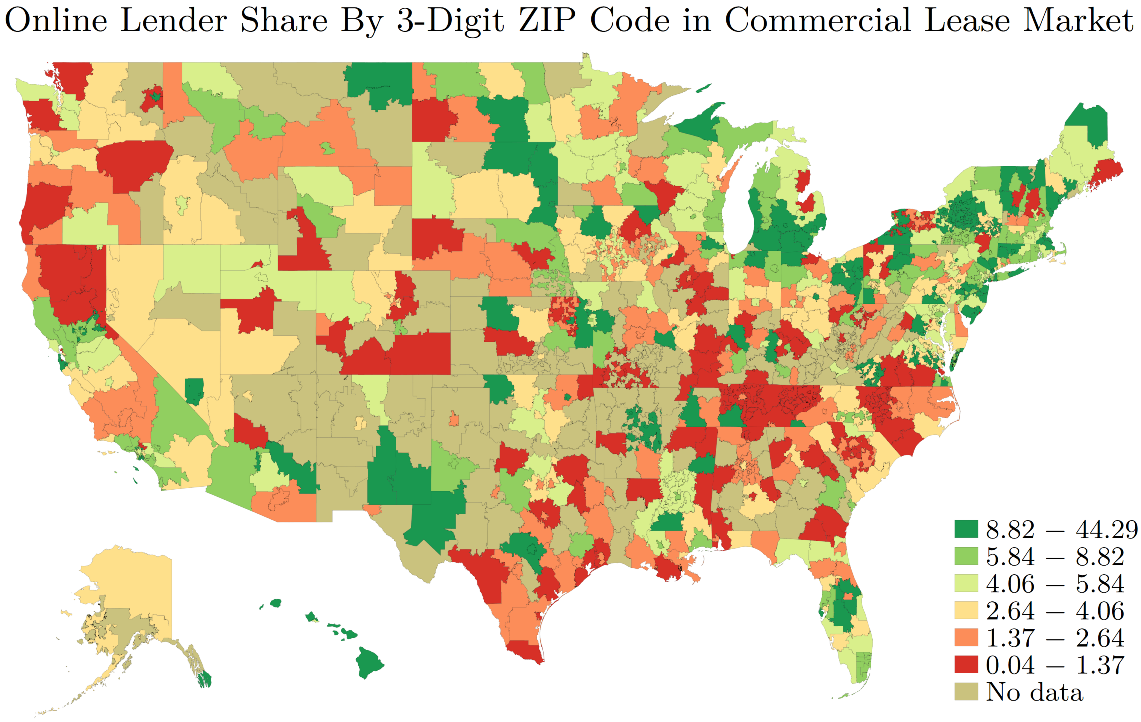

Figure 6

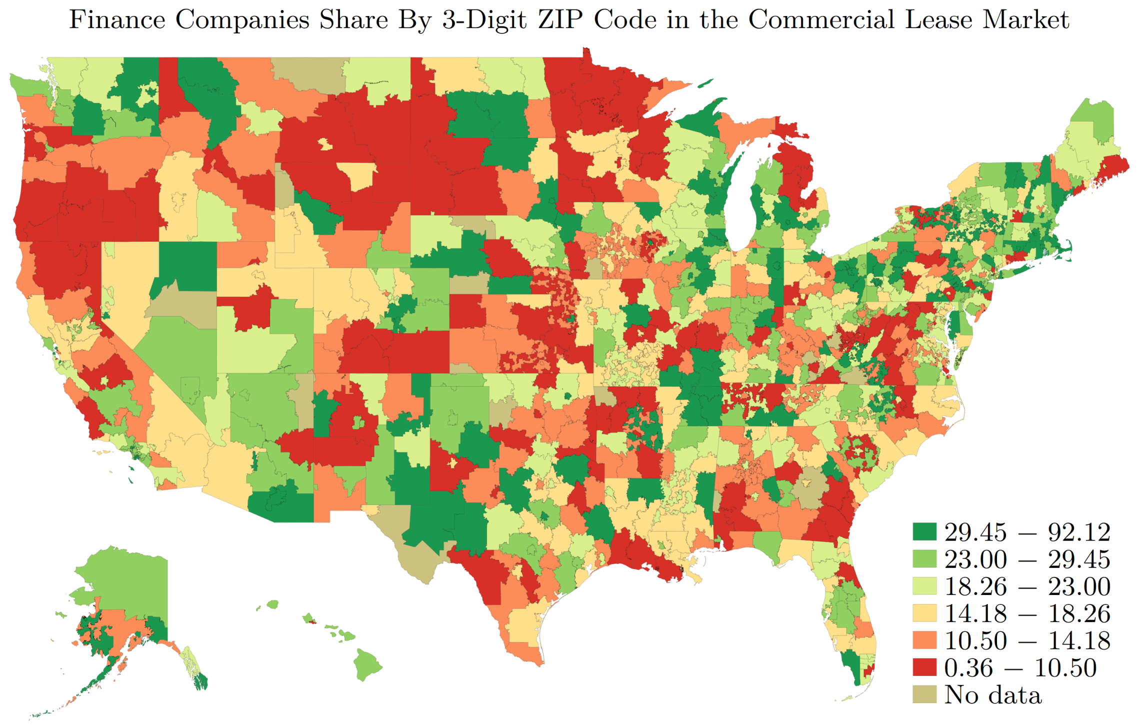

Figure 7

Finance Companies Share By 3-Digit ZIP Code in the Lines of Credit Market

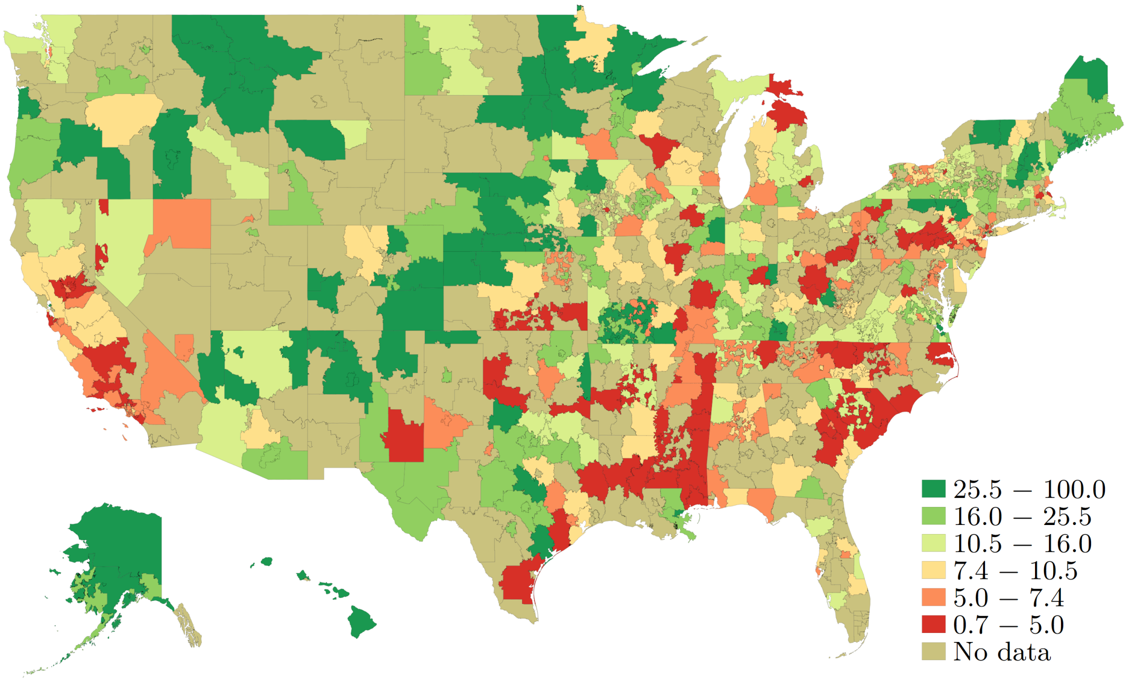

Figure 8

Finance Companies Share By 3-Digit ZIP Code in the Term Loan Market

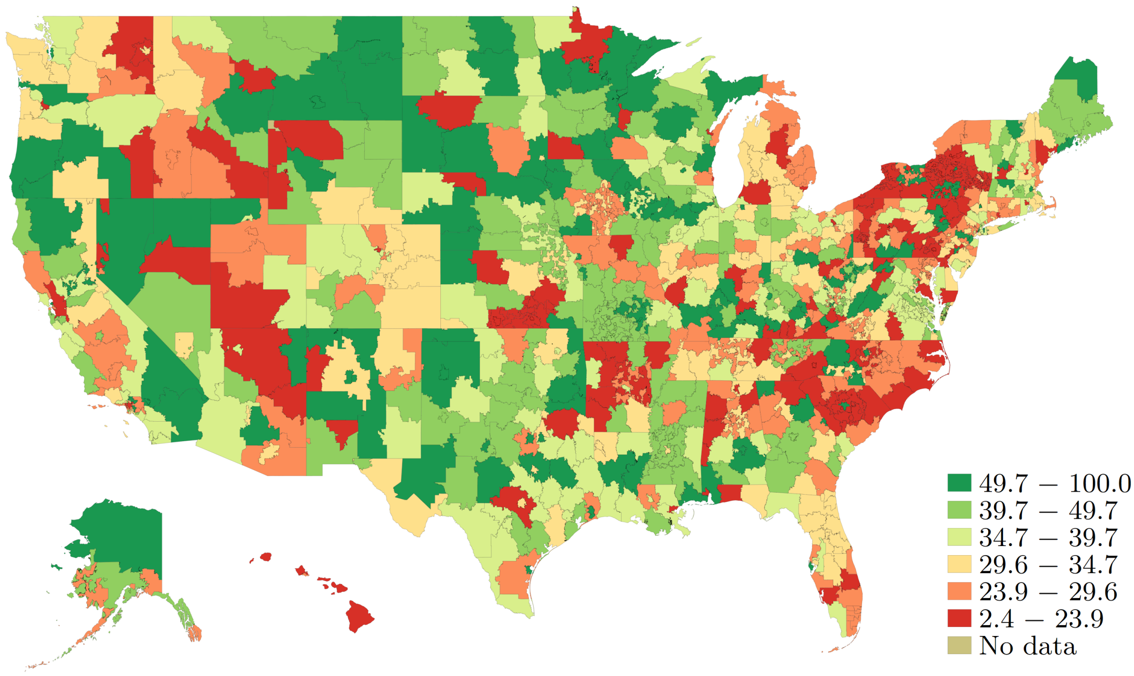

Figure 9

Bank and Credit Unions Share By 3-Digit ZIP Code in Term Loan Market

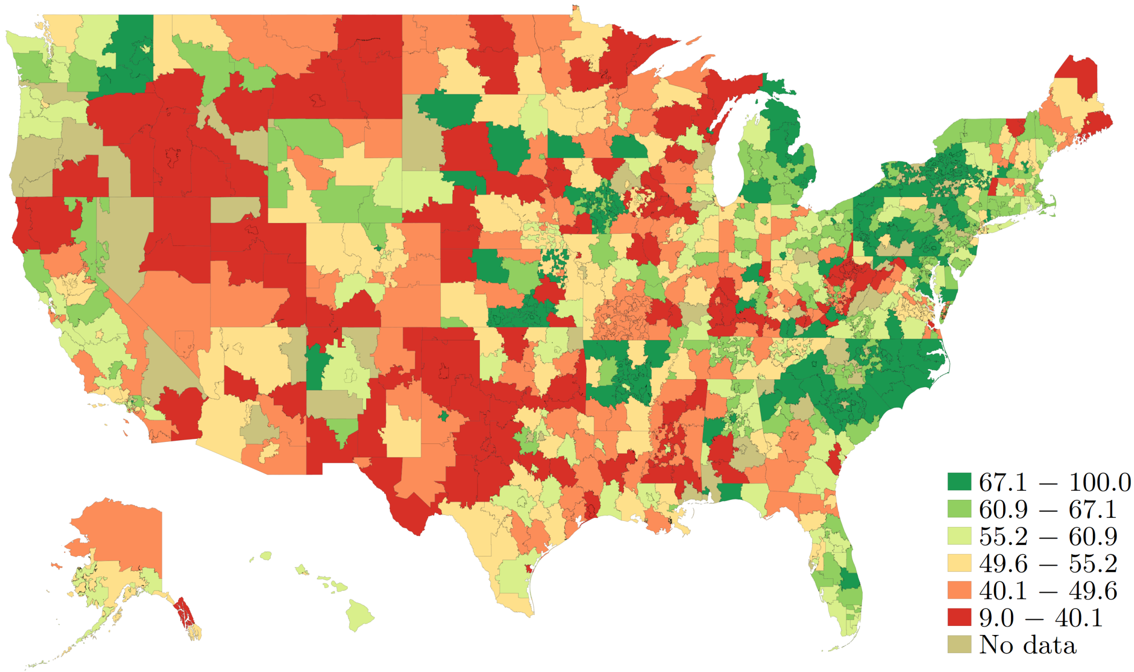

Figure 10

Bank and Credit Unions Share By 3-Digit ZIP Code in the Commercial Lease Market

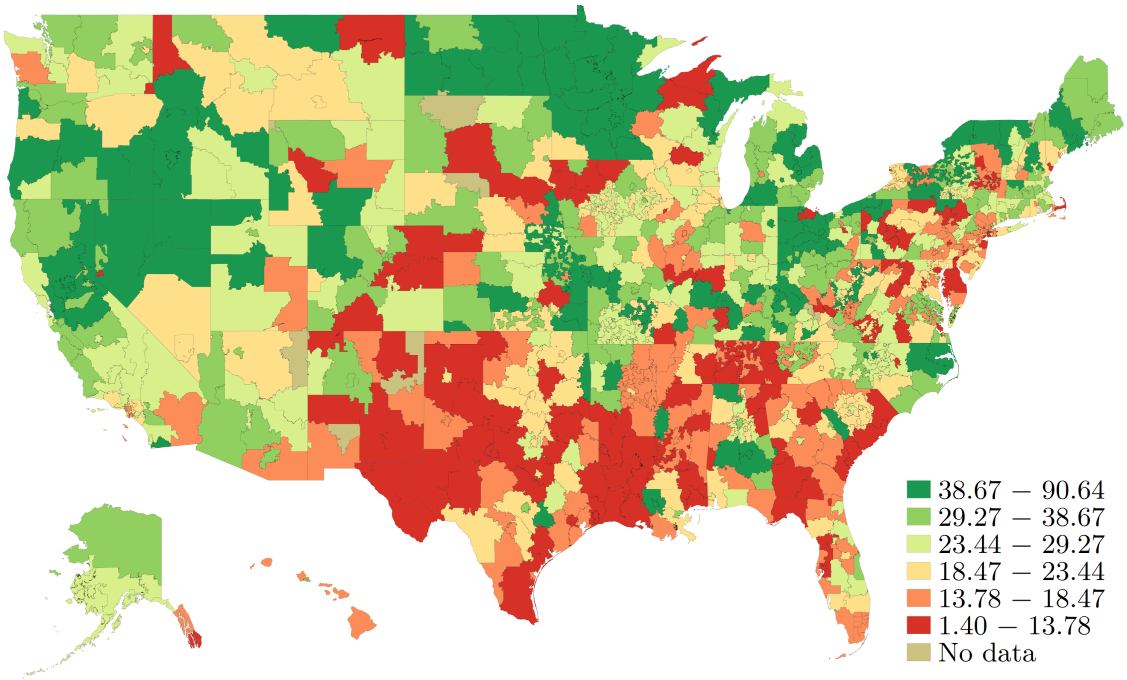

Figure 11

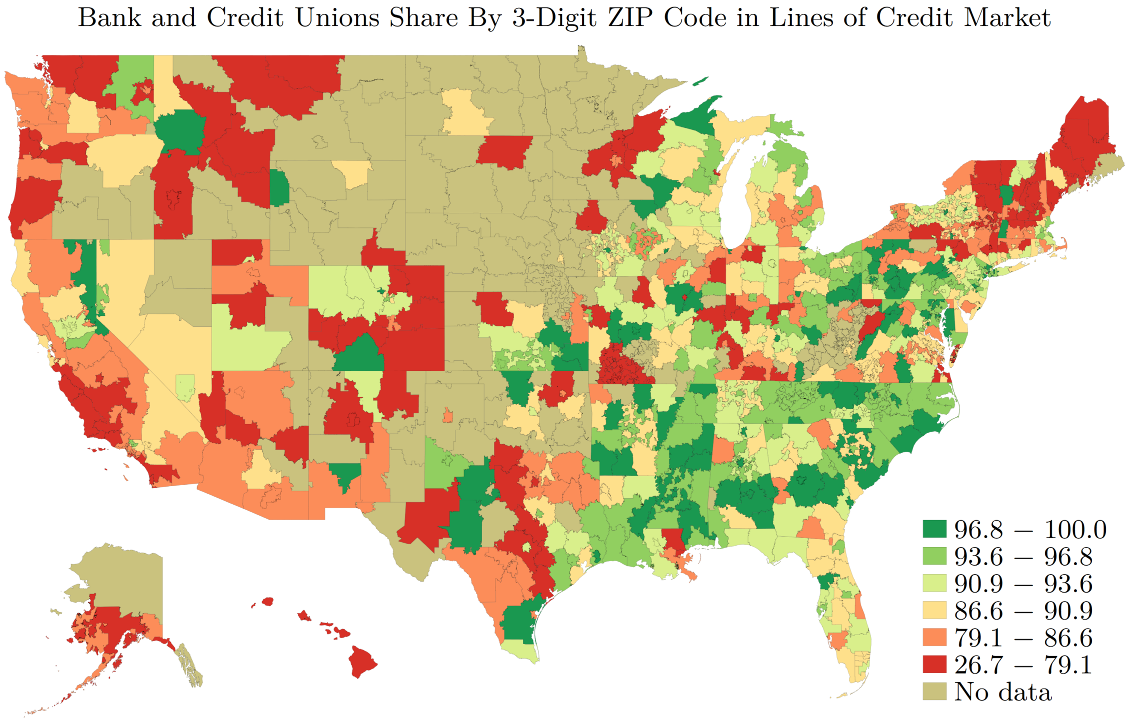

Figure 12

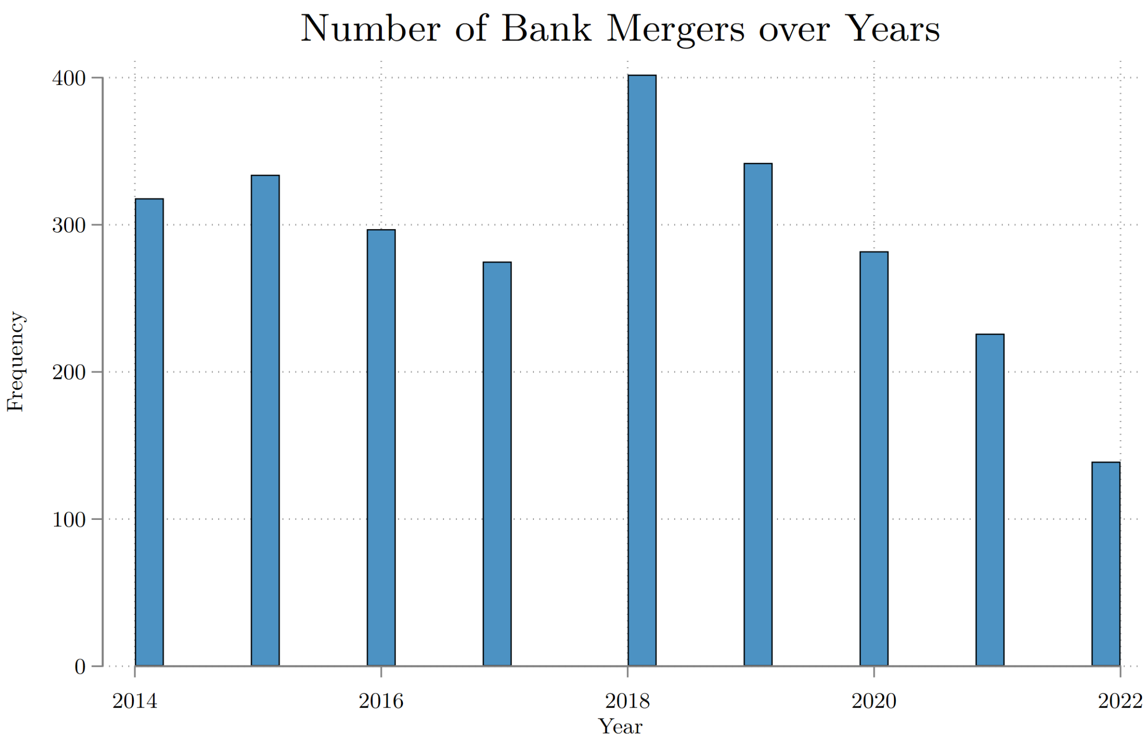

Figure 13: This figure depicts the number of depository financial institution mergers throughout from 2014 to 2022. The calculations are using FDIC Bank Suit Event and Changes.

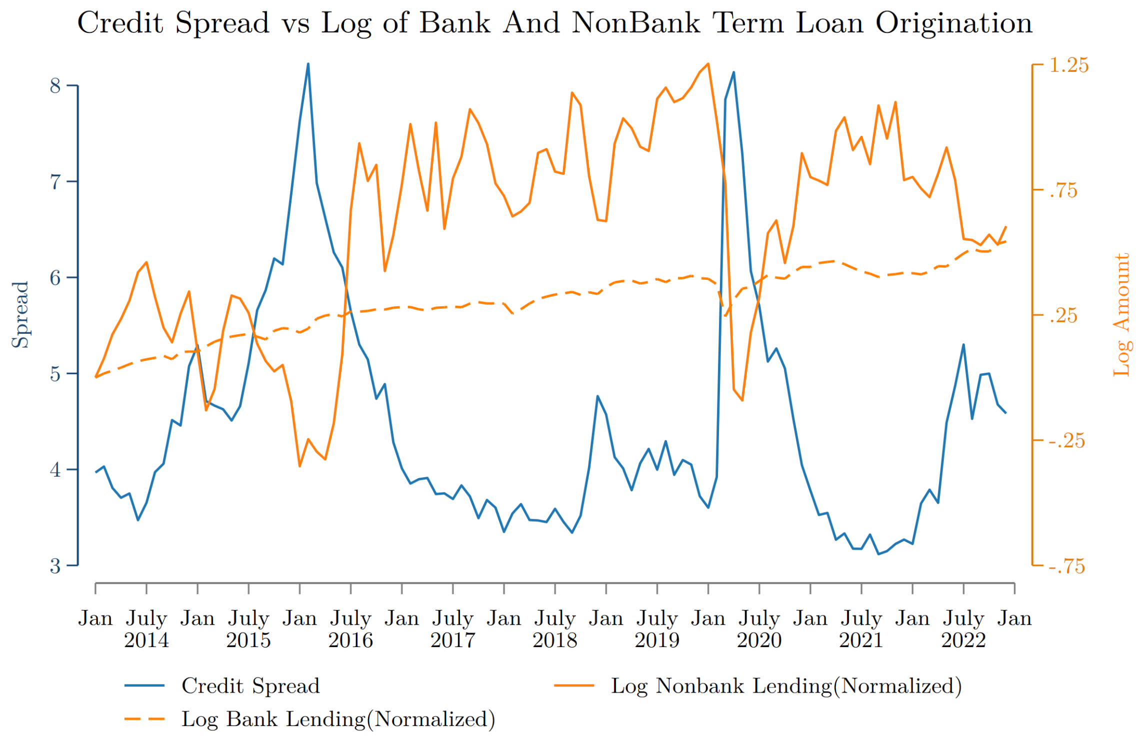

Figure 14: Note: This figure depicts ICE BofA US High Yield Index Option-Adjusted Spread(left axis) and Normalized Bank and Nonbank of newly originated loans (right axis). The data is normalized to have a starting position of zero. Original data for credit spread is at the daily level and is for the years 2014 through 2022. The depicted credit spread graph uses the monthly average of the original data.

8 Tables

Table 1: Business Level Summary Statistics

This table provides summary statistics for the variables used in the analysis for small business, provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. Numbers greater than ten are rounded. Numbers between 1 and 10 have one decimal digit. Numbers less than one have two digits after zeros. An ending zero-digit is also dropped.

	mean	sd	p5	p25	p50	p75	p90	p95
Annual Sales Amount (Thousands)	940	1195	63	196	459	1,077	2,611	4,688
Number of Employees(Excl Zero)	7.4	8.6	1	2	4	8	18	35
Number of Employees	1.7	3.2	0	0	2	7	25	50
Credit Score	31	28	4	10	13	54	78	89
Judgments Filed	.011	.12	0	0	0	0	0	0
Total Dollar Amount of legal Liability	1,384	16,769	0	0	0	0	0	0
Lien Count	.095	.81	0	0	0	0	0	0
Number of Derogatory Record Filings	.12	.89	0	0	0	0	0	0
Total Number of Legal Item	.69	3	0	0	0	0	2	4
Total Account Balance	27,944	177,338	100	200	1,200	7,000	31,200	79,700
Total Combined Trade	7.6	6.8	2	3	6	9	15	20
UCC Count	4.8	8	1	1	2	5	10	16
Years In Vendor dataset	14	9.7	2	6	11	19	28	33
Business Start Year	2,006	9.8	1,987	2,000	2,009	2,013	2,016	2,018
Bankruptcy Filed (Dummy)	.0049	.07	0	0	0	0	0	0
Collection Count	.04	.27	0	0	0	0	0	0
DBT For New And Continuous Trades	3.6	18	0	0	0	0	0	12
Total Number of Bankruptcy Filings	.0048	.069	0	0	0	0	0	0
Total Number of Bankruptcies Filed Within 24 Months	.00077	.041	0	0	0	0	0	0
Most Recent Bankruptcy Filing Age in Months	64	30	10	41	69	94	98	98

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Table 1: (Continued) Business Level Summary Statistics

	mean	sd	p5	p25	p50	p75	p90	p95
Percentage of Trade Balance To Total Highest Balance In Past 12 Months	67	36	5	33	85	100	100	100
Percentage of Total Number of Aged Trades To Total Number of Total Trades	66	32	20	33	50	100	100	100
Age, In Months, of Oldest Commercial Banking Relationship	117	100	5	42	92	162	245	326
Average Age, In Months, of Commercial Banking Relationsh	115	1.0e+02	5	41	89	160	242	323
Total Account Balance For Commercial Banking Relationships	2,265,600	5,011,773	1,107	22,167	415,810	1,755,562	6,388,111	12,395,279
Total Account Balance For Commercial Banking Relationships In The Past 12 Months	2,629,016	5,266,845	1,544	77,098	631,729	2,468,643	7,154,745	13,953,505
Total Number of Open And Closed Collection Trades	.04	.27	0	0	0	0	0	0
Age, In Months, of Most Recent Collection Trade	1.1	7.2	0	0	0	0	0	0
Age, In Months, of Most Recent Open Collection Trade	.64	5.6	0	0	0	0	0	0
Total original amount for all leasing trades	31,282	63,505	3,600	7,200	13,528	29,732	66,428	110,339
Percentage of total Amount of Leasing trades to total balance of trades	32	28	2	8	23	51	77	88
Days Beyond Terms of new trades	.031	.66	0	0	0	0	0	0
Total balance of new trades	16,996	121,540	100	100	400	2,500	23,700	52,700
Total highest balance in past 12 months across all new trades	17,095	118,206	100	100	400	2,700	24,100	54,100
Total balance of other trades classified as Leasing	8,552	26,202	100	700	2,500	7,800	18,800	30,700
Total balance of other trades classified as Supplemental	12,762	58,508	100	200	1,200	5,700	24,500	51,500
Annual Sales Per Employee (Thousands)	173	206	32	65	115	187	334	558

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Table 2: Trade(loan) Summary Statistics

This table provides summary statistics for the variables used in the analysis for small business loans provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 0.99% levels. Numbers greater than ten are rounded. Numbers between 1 and 10 have one decimal digit. Numbers less than one have two digits after zeros. An ending zero-digit is also dropped.

	mean	sd	p5	p10	p25	p50	p75	p90	p95
Panel A:Finance:									
Amount	24,812	49,401	1,250	2,088	5,000.0	12,000	25,000	48,302	72,769
Balance	14,871	38,458	81	146	484.4	2,231	10,247	33,787	67,382
Utilization	32	31	.9	1.8	5.8	20	53	86	94
Loan Term(Y)	8.1	6.8	.83	1.4	3.1	5.4	12	18	22
Panel B:Term loan:									
Amount	63,762	88,726	4,100	9,800	22,419	35,639	56,450	144,200	320,875
Balance	47,444	66,040	342	997	7,263	22,239	49,188	155,315	238,436
Balance/Amount	58	32	4.5	9.2	30	64	88	97	99
Loan Term(Y)	3.7	2.9	.42	.75	1.8	3.4	5	6.1	8.8
Panel C:Commercial Lease:									
Amount	29,946	30,359	7,909	10,279	14,795	21,338	35,532	55,389	72,750
Balance	16,034	33,700	204	450	1,550	5,109	14,373	37,470	68,283
Balance/Amount	51	30	4.7	9	24	53	80	91	95
Loan Term(Y)	3.8	1.9	.75	1.3	2.7	3.6	5	6.5	6.8
Panel D:Line of Credit:									
Amount	70,691	107,646	1,278	2,316	6,287	25,000	75,000	240,294	400,000
Balance	31,226	61,217	95	178	633	3,568	26,705	99,899	238,436
Credit Utilization	50	33	1.5	4.4	18	49	81	95	99
Panel E:Credit Card:									
Amount	17,650	18,018	1,881	3,000	6,476	13,032	22,558	35,100	50,000
Balance	4,829	8,384	82	153	548	1,907	5,501	12,549	19,241
Credit Utilization	28	28	.7	1.5	5.5	18	44	77	89

Table 3: Trade(loan) Summary Statistics for Online Lenders

This table provides summary statistics for the online lenders subsample for variables used in the analysis for small businesses, provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels.Numbers greater than ten are rounded. Numbers between 1 and 10 have one decimal digit. Numbers less than one have two digits after zeros. An ending zero-digit is also dropped.

	mean	sd	p5	p10	p25	p50	p75	p90	p95
Panel A:Finance:									
Amount	39,426	24,046	14,000	18,222	25,698.0	36,034	48,379	62,143	71,647
Balance	25,352	21,537	2,231	4,122	10,447.5	21,451	35,000	49,661	59,967
Utilization	61	30	8	14	36.1	66	88	96	98
Loan Term(Y)	3.4	1.6	.5	1	2.3	3.3	4.9	5.1	5.3
Panel B:Term loan:									
Amount	41,004	24,476	16,712	20,969	27,583	37,322	49,333	62,889	72,458
Balance	26,549	21,998	2,635	4,794	11,628	22,776	36,130	50,926	61,322
Balance/Amount	62	30	8.3	14	38	68	90	97	99
Loan Term(Y)	3.4	1.6	.42	1	2.3	3.7	5	5.1	5.3
Panel C:Commercial Lease:									
Amount	29,752	18,484	10,200	12,068	16,296	23,540	39,343	54,926	66,532
Balance	17,239	15,877	1,078	1,914	5,486	12,919	24,271	39,361	47,704
Balance/Amount	54	29	6.4	11	28	58	81	91	95
Loan Term(Y)	2.9	1.1	1.1	1.7	2.4	3	3.3	4.3	5.1

Table 4: Trade(loan) Summary Statistics for Finance Companies (Including Online Lenders)

This table provides summary statistics for the Finance Companies (including online lenders) for variables used in the analysis for small businesses, provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. Numbers greater than ten are rounded. Numbers between 1 and 10 have one decimal digit. Numbers less than one have two digits after zeros. An ending zero-digit is also dropped.

	mean	sd	p5	p10	p25	p50	p75	p90	p95
Panel A:Finance:									
Amount	31,340	30,212	2,500	5,000	12,006.0	26,614	42,149	58,678	71,516
Balance	25,252	39,996	184	426	2,363.6	12,393	30,989	56,908	91,675
Utilization	48	34	2.2	4.4	14.3	47	80	94	97
Loan Term(Y)	3.8	2.5	.58	1	2.2	3.4	5	5.8	8.7
Panel B:Term loan:									
Amount	34,751	31,556	2,000	4,400	16,044	31,244	45,530	61,789	75,699
Balance	32,011	44,681	201	512	5,177	19,538	38,267	68,788	118,152
Balance/Amount	51	34	2.8	5.3	17	52	83	95	98
Loan Term(Y)	3.6	2.2	.5	.92	2	3.5	4.9	5.3	6.8
Panel C:Commercial Lease:									
Amount	26,883	20,596	8,944	10,727	14,553	20,850	33,158	51,195	62,364
Balance	13,546	22,610	331	628	1,975	6,581	16,061	32,240	46,841
Balance/Amount	54	30	6.8	11	27	57	82	92	95
Loan Term(Y)	3.3	1.4	1	1.5	2.3	3.1	4.3	5.2	5.3
Panel D:Line of Credit:									
Amount	130,893	131,746	15,032	20,000	35,000	70,000	200,000	400,000	400,000
Balance	10,514	33,339	330	597	1,559	3,162	4,960	10,765	41,862
Credit Utilization	53	33	6.9	10	18	53	85	96	99
Panel E:Credit Card:									
Amount	11,331	6,588	2,788	3,998	6,363	10,000	15,400	20,000	23,900
Balance	2,177	2,986	52	103	318	1,051	2,826	5,681	8,174
Credit Utilization	21	24	.55	1.1	3.6	11	30	60	77

Table 5: Trade(loan) Summary Statistics for Bank and Credit Union Lenders

This table provides summary statistics for bank and credit unions subsample for variables used in the analysis for small businesses, provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. Numbers greater than ten are rounded. Numbers between 1 and 10 have one decimal digit. Numbers less than one have two digits after zeros. An ending zero-digit is also dropped.

	mean	sd	p5	p10	p25	p50	p75	p90	p95
Panel A:Finance:									
Amount	55,951	89,756	4,013	7,091	15,000.0	25,101	48,024	123,820	324,508
Balance	35,617	62,300	215	448	1,792.5	9,551	33,493	112,077	238,436
Utilization	42	35	1.2	2.5	8.5	34	77	94	98
Loan Term(Y)	6.2	5	.83	1.3	2.9	4.8	8.4	15	16
Panel B:Term loan:									
Amount	80,642	105,583	11,454	17,052	25,849	39,501	67,823	250,000	400,000
Balance	60,777	75,289	2,543	5,044	13,027	27,696	65,799	238,436	238,436
Balance/Amount	64	30	8.4	16	41	71	91	97	99
Loan Term(Y)	4.2	3.3	.58	.92	1.9	3.8	5.1	7.2	10
Panel C:Commercial Lease:									
Amount	27,443	19,335	9,979	11,920	16,800	21,025	32,869	48,156	62,991
Balance	25,779	44,126	704	1,307	3,553	9,237	25,098	67,988	117,874
Balance/Amount	49	30	4.8	8.4	21	48	76	89	94
Loan Term(Y)	3.7	1.4	1.2	1.8	2.9	3.8	4.9	5.2	5.5
Panel D:Line of Credit:									
Amount	107,780	124,163	4,100	9,980	25,000	50,000	125,000	400,000	400,000
Balance	65,375	77,980	522	2,167	9,851	30,528	87,817	238,436	238,436
Credit Utilization	60	32	3.2	11	34	66	90	98	1.0e+02
Panel E:Credit Card:									
Amount	18,440	14,109	3,179	5,000	10,000	16,000	25,000	32,200	41,000
Balance	2,883	5,182	110	173	425	1,194	3,141	7,001	11,372
Credit Utilization	17	21	.71	1.3	3.3	8.7	21	46	70

Table 6: Trade(loan) Summary Statistics for Manufacturers and Leasing Company Lenders

This table provides summary statistics for manufacturers and leasing company subsamples for variables used in the analysis for small businesses, provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. Numbers greater than ten are rounded. Numbers between 1 and 10 have one decimal digit. Numbers less than one have two digits after zeros. An ending zero-digit is also dropped.

	mean	sd	p5	p10	p25	p50	p75	p90	p95
Panel A:Finance:									
Amount	11,837	29,221	1,000	1,500	3,000.0	7,000	12,000	21,800	28,500
Balance	11,425	33,962	65	108	294.2	1,217	6,277	23,337	52,865
Utilization	22	27	.8	1.3	3.3	9.7	30	69	87
Loan Term(Y)	8.4	7.8	.67	1.3	3.1	5	13	21	25
Panel B:Term loan:									
Amount	56,298	93,199	10,421	15,500	20,498	26,796	37,423	100,000	400,000
Balance	43,985	68,036	266	501	2,385	14,807	45,054	160,800	238,436
Balance/Amount	59	30	7.9	12	36	63	87	96	98
Loan Term(Y)	3.2	2.7	.17	.33	1.1	3.1	4.1	5.4	7.3
Panel C:Commercial Lease:									
Amount	59,101	64,920	3,628	7,015	16,821	36,336	76,727	142,274	197,253
Balance	16,241	35,131	171	376	1,558	5,130	13,858	36,820	69,626
Balance/Amount	44	35	.58	1.6	6.1	44	79	92	96
Loan Term(Y)	3.5	1.8	.58	1.2	2.5	3.5	4.8	5.3	5.8
Panel D:Line of Credit:									
Amount	85,988	83,657	13,000	20,000	30,000	55,000	100,000	200,000	250,000
Balance	4,010	14,922	50	90	239	698	2,104	6,692	15,688
Credit Utilization	52	31	4.8	11	26	50	80	96	99
Panel E:Credit Card:									
Amount	15,788	8,681	3,935	6,100	11,000	15,000	20,100	25,000	26,300
Balance	2,995	4,839	66	107	310	1,125	3,707	8,337	12,219
Credit Utilization	20	25	.48	.85	2.5	9.1	29	60	82

Table 7: Lender Type Transition Matrix (Conditional on a Firm Getting a Loan)

This table shows the transition matrix of lenders of a business. Panel A provides a simple transition matrix where each row represents the type of the latest previous lender, and each column represents the latest lender type. The extended matrix conditions on the last two relationships. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels.

Next Lender:	Bank	Finance Online	Finance Others	NonFinance
Panel A: Transition Matrix Depending on the last relationship				
Bank	0.74	0.14	0.05	0.07
Online	0.10	0.78	0.04	0.08
Other Finance	0.09	0.13	0.72	0.06
NonFinance	0.08	0.15	0.06	0.71
Panel B:Transition Matrix-Extended History:Last Two Relationship				
Bank-Bank	0.78	0.07	0.10	0.05
Bank-Non Finance	0.41	0.39	0.12	0.08
Bank-Finance Online	0.47	0.08	0.37	0.08
Bank-Finance Other	0.10	0.06	0.09	0.75
Non Finance-Bank	0.78	0.06	0.11	0.05
Non Finance-Non Finance	0.11	0.72	0.11	0.06
Non Finance-Finance Online	0.18	0.25	0.48	0.09
Non Finance-Finance Other	0.10	0.07	0.10	0.73
Finance Online-Bank	0.78	0.06	0.11	0.05
Finance Online-Non Finance	0.17	0.47	0.27	0.09
Finance Online-Finance Online	0.12	0.08	0.74	0.06
Finance Online-Finance Other	0.10	0.07	0.10	0.73
Finance Other-Bank	0.79	0.06	0.10	0.05
Finance Other-Non Finance	0.14	0.39	0.12	0.35
Finance Other-Finance Online	0.15	0.08	0.37	0.40
Finance Other-Finance Other	0.10	0.07	0.09	0.74

Table 8: Exposure to Merger and the Probability of Branch Closing for Different Time Horizons

This table shows estimates of equation

$$\text{Closed}_{b,a,t+\tau} = \gamma \text{Exposure}_{b,t,a} + \text{FEs} + \text{Controls} + \nu_{i,b,a,t+\tau}$$

where t denotes the current time. a denotes zipcode. g is lender type and, $\mathcal{G}$ denotes the set of lender types shown in the first column of the table. a denotes the region the business is located at. b is bank. The regression is run at the monthly level. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Closed denotes the cumulative number of closings relative to time t. Region Chars contains different time-varying regional characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The data covers the period 2014 through 2022. All results are relative to the month -1. Business level characteristics are provided at the yearly level, and loan performance data is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels.

τ :	-12	3	6	9	12	18	24
Exposure	0.009	0.052*	0.101***	0.174***	0.224***	0.232***	0.236***
	(0.16)	(2.05)	(3.54)	(6.02)	(8.12)	(8.02)	(7.71)
Time Varying Region Chars	Y	Y	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y	Y
Observations	249.8MM	235.9MM	228.4MM	220.2MM	212.4MM	205.6MM	198.6MM
R^2	0.39	0.44	0.43	0.43	0.42	0.42	0.42

t-statistics are in parentheses

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 9: Bank Branch Closing and Loan Characteristics, Second Stage Results

This table shows estimates of equation

$$Y_{i,b,a,t,g} = \sum_{s \in \mathcal{G}} \alpha_s \text{Closed}_{b,t,a} \times 1\{g=s\} + \text{FEs} + \beta \text{Region Chars}_{t-12} + \theta \text{Borrower Chars}_{t-12} + \varepsilon_{i,b,a,t,g}$$

where t denotes the current time. i denotes the firm. a denotes zipcode. g is lender type and, $\mathcal{G}$ denotes the set of lender types shown in the first column of the table. a denotes the region the business is located at. b is bank(previous lender). The regression is run at the monthly level. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Loan Num denotes the number of loans given in the last 12 months. Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken in the past twelve months. Closed denotes the cumulative number of closings relative to time $t-12$. Each unit of observation is at the borrower-period-previous lender-lender type level. The regressions are IVed by the 12-month lag of the Exposure variable. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Region Chars contains different time-varying regional characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance data is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels

	Loan Num	Log Loan Am	APR(%)	Log Limit	ΔLog Limit (Existing)	Normalized Total Lending (Incl. 0)
α						
Same Lender	-0.10***	-0.05***	0.32*	-0.04**	-0.01*	-0.24***
	(-12.03)	(-8.75)	(2.15)	(-2.69)	(-2.47)	(-8.42)
Other Bank lenders	0.04***	-0.02**	0.42**	-0.07**		0.06**
	(6.02)	(-3.12)	(3.03)	(-3.12)		(2.73)
Nonbanks	0.04***	-0.01*	0.65***			0.08***
	(6.85)	(-2.43)	(4.23)			(4.03)
Time Varying Region Chars	Y	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
δ_b(Prev Lender FE)	Y	Y	Y	Y	Y	Y
δ_g(Lender Type FE)	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	212.4MM	9.3MM	8.9MM	2.7MM	4.2MM	211.3MM
Adj R^2	0.44	0.45	0.47	0.45	0.44	0.44

t-statistics are in parentheses
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 10: Bank Branch Closing and Borrowing Activity, Depending on the Number of Previous Lenders of a Business, Second Stage Result

This table shows estimates of equation

$$\begin{aligned} Y_{i,b,a,t,g} &= \sum_{s\,\in\mathcal{G}} \beta_s \text{Closed}_{b,t,a} \times 1\{g=s\} \times \text{Only one main lender} \\ &+ \sum_{s\,\in\mathcal{G}} \alpha_s \text{Closed}_{b,t,a} \times 1\{g{=}s\} + \text{FEs} + \text{Controls} + \varepsilon_{i,b,a,t,g} \end{aligned} \tag{6}$$

t denotes the current time. a denotes zipcode and b is bank. g is lender type and $\mathcal{G}$ = {Same Lender,Other banks,Finance Nonbank} is the set of lender types. The regression is run at the monthly level. Loan Num denotes the number of loans given in the last 12 months. Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken in the past twelve months. Each unit of observation is at the borrower-period-previous lender-lender type level. The regressions are IVed by the 12-month lag of the Exposure variable. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Only one main lender denotes whether the business has had only one main lender. A main lender is defined as a lender that has a positive loan balance in the borrower's trade file or has lent in the past three years. Each unit of observation is at the borrower-period-previous lender-lender type level. Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The dataset contains FDIC SOD and Event and Changes in Bank Suite and the large dataset of loans to small businesses provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels.

	Loan Num	Log Loan Am	APR(%)	Log Limit	ΔLog Limit (Existing)	Normalized Total Lending
α_s						
Same Lender	-0.13***	-0.03***	0.12	-0.03**	-0.01*	-0.27***
	(-9.56)	(-5.09)	(1.74)	(-3.02)	(-2.07)	(-9.05)
Other Bank lenders	0.07***	-0.01	0.01	-0.00		0.13***
	(5.49)	(-1.89)	(0.18)	(-0.72)		(4.74)
Nonbanks	0.05**	-0.01	0.17			0.08**
	(3.14)	(-1.01)	(1.42)			(2.62)
Interaction Terms(β_s)						
Same Lender	0.06***	-0.04***	0.40**	-0.02**	-0.00	0.08**
	(5.64)	(-4.98)	(3.21)	(-2.69)	(-1.47)	(3.03)
Other Bank lenders	-0.05**	-0.02***	0.99***	-0.07***		-0.11***
	(-3.03)	(-4.34)	(7.83)	(-4.12)		(-4.82)
Nonbanks	-0.00	-0.00	1.45***			-0.00
	(-0.73)	(-0.89)	(9.23)			(-0.16)
Time Varying Region Chars	Y	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
δ_b(Prev Lender FE)	Y	Y	Y	Y	Y	Y
δ_g(Lender Type FE)	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	212.1MM	9.3MM	8.9MM	2.7MM	4.2MM	211.3MM
Adj R^2	0.45	0.47	0.48	0.46	0.45	0.46

t-statistics are in parentheses

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 11: Bank Closing and Borrowing Activity for Smaller Borrowers, Second Stage Result

This table shows estimates of equation

$$
\begin{aligned}
Y_{i,b,a,t,g} = \sum_{s\,\in\mathcal{G}} \beta_s \text{Closed}_{b,t,a} \times 1\{g=s\} \times 1(\#\text{Employees} > 4) + \sum_{s\,\in\mathcal{G}} \alpha_s \text{Closed}_{b,t,a} \\
\times 1\{g=s\} + \text{FEs} + \beta \text{Region Chars}_{t-12} + \theta \text{Borrower Chars}_{t-12} + \varepsilon_{i,b,a,t,g}
\end{aligned} \tag{7}
$$

t denotes the current time. a denotes zipcode and b is bank. Loan Num denotes the number of loans given in the last 12 months. Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken in the past twelve months. Each unit of observation is at the borrower-period-previous lender-lender type level. The regressions are IVed by the 12-month lag of the Exposure variable. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Each unit of observation is at the borrower-period-previous lender-lender type level. Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The dataset contains FDIC SOD and Event and Changes in Bank Suite and the large dataset of loans to small businesses provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels

	Loan Num	Log Loan Am	APR(%)	Log Limit	ΔLog Limit (Existing)	Log Sales	Log Employment	Normalized Total Lending (Incl. 0)
Panel A: Loan Outcomes								
α_s								
Same Lender	-0.12***	-0.06***	0.51*	-0.05***	-0.02			-0.29***
	(-7.69)	(-7.87)	(2.23)	(-4.33)	(-1.86)			(-8.49)
Other Bank Lenders	0.04***	-0.02***	0.91***	-0.11***				0.06**
	(5.08)	(-3.92)	(6.75)	(-8.84)				(3.16)
Nonbanks	0.02**	-0.02***	1.23***					0.02
	(3.24)	(-3.68)	(8.95)					(1.23)
Interaction Terms:								
Same Lender	0.03***	0.02***	-0.36*	0.02**	0.02*			0.08***
	(4.12)	(4.87)	(-2.15)	(2.69)	(2.47)			(4.73)
Other Bank lenders	0.00	0.00	-0.79***	0.08***				0.01
	(1.13)	(1.06)	(-5.83)	(5.12)				(0.91)
Nonbanks	0.04***	0.02***	-0.78***					0.05***
	(4.75)	(4.39)	(-5.23)					(5.05)
Panel B: Real Outcomes (No Lender Type):								
Closed× Big						0.02*	0.03	
						(2.02)	(1.89)	
Closed						-0.02**	-0.03**	
						(-2.98)	(-2.74)	
Time Varying Region Chars	Y	Y	Y	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
δ_b(Prev Lender FE)	Y	Y	Y	Y	Y	Y	Y	Y
δ_g(Lender Type FE)	Y	Y	Y	Y	Y	N	N	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	212.1MM	9.3MM	8.9MM	2.7MM	4.2MM	52.4MM	31.9MM	211.3MM
Adj R^2	0.45	0.46	0.49	0.46	0.44	0.38	0.35	0.44

t-statistics are in parentheses
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 12: Bank Closing and Loan Activity across Credit Cycles, Second Stage Result

This table shows estimates of equation

$$
\begin{aligned}
Y_{i,b,a,t,g} = \sum_{s\,\in\mathcal{G}} \beta_s \text{Closed}_{b,t,a} \times 1\{g = s\} \times \text{Credit Cycle} + \sum_{s\,\in\mathcal{G}} \alpha_s \text{Closed}_{b,t,a} \\
\times 1\{g{=}s\} + \text{FEs} + \beta \text{Region Chars}_{t-12} + \theta \text{Borrower Chars}_{t-12} + \varepsilon_{i,b,a,t,g}
\end{aligned} \tag{8}
$$

t denotes the current time. a denotes zipcode and b is bank. Loan Num denotes the number of loans given in the last 12 months. Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken in the past twelve months. Each unit of observation is at the borrower-period-previous lender-lender type level. The regressions are IVed by the 12-month lag of the Exposure variable. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Each unit of observation is at the borrower-period-previous lender-lender type level. Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The dataset contains FDIC SOD and Event and Changes in Bank Suite and the large dataset of loans to small businesses provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. The credit cycle is derived by scaling credit spread to have a minimum and maximum of -1 and 1. All variables are winsorized at 0.1% and 99.9% levels

	Loan Num	Log Loan Am	APR(%)	Log Limit	ΔLog Limit (Existing)	Normalized Total Lending (Incl. 0)
Panel A: Loan Outcomes						
α_s						
Same Lender	-0.10***	-0.05***	0.29*	-0.05***	-0.02*	-0.23***
	(-8.49)	(-7.69)	(2.31)	(-3.87)	(-2.41)	(-9.12)
Other Bank lenders	0.04***	-0.02***	0.49**	-0.09***		0.06***
	(7.03)	(-3.77)	(2.83)	(-5.12)		(3.78)
Nonbanks	0.04***	-0.00	0.65***			0.09***
	(8.75)	(-1.63)	(4.23)			(9.24)
Interaction Terms:						
Same Lender× Credit Cycle	0.00	-0.01	0.14	-0.03*	-0.01	-0.00
	(0.94)	(-1.68)	(0.94)	(-2.05)	(-1.82)	(-0.31)
Other Bank lenders× Credit Cycle	-0.01	-0.01*	0.28*	-0.03*		-0.03*
	(-1.91)	(-2.13)	(2.02)	(-2.47)		(-2.15)
Nonbanks× Credit Cycle	-0.03***	-0.01**	0.39**			-0.07***
	(-4.68)	(-2.83)	(3.13)			(-4.22)
Time Varying Region Chars	Y	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
δ_b(Prev Lender FE)	Y	Y	Y	Y	Y	Y
δ_g(Lender Type FE)	Y	Y	Y	Y	Y	Y
Observations	212.1MM	9.7MM	8.9MM	2.5MM	4.2MM	211.3MM
Adj R^2	0.46	0.47	0.49	0.45	0.46	0.49

t-statistics are in parentheses
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 13: Bank Closing, New Loan Activity During COVID Crisis, Second Stage Results

This table shows estimates of equation

$$Y_{i,b,a,t,g} = \sum_{s \in \mathcal{G}} \beta_s \text{Closed}_{b,t,a} \times 1\{g=s\} \times 1(\text{Pre COVID}) + \sum_{s \in \mathcal{G}} \alpha_s \text{Closed}_{b,t,a}$$
$$\times 1\{g=s\} + \delta_i + \text{FEs} + \beta \text{Region Chars}_{t-12} + \theta \text{Borrower Chars}_{t-12} + \varepsilon_{i,b,a,t,g}$$

t denotes the current time. a denotes zipcode and b is bank. Loan Num denotes the number of loans given in the last 12 months. Only years 2017-2022 are used. Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken in the past twelve months. Each unit of observation is at the borrower-period-previous lender-lender type level. The regressions are IVed by the 12-month lag of the Exposure variable. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Each unit of observation is at the borrower-period-previous lender-lender type level. Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The dataset contains FDIC SOD and Event and Changes in Bank Suite and the large dataset of loans to small businesses provided by one of the credit bureaus. The data covers the period 2017 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels

	Loan Num	Log Loan Am	APR(%)	Log Limit	ΔLog Limit (Existing)	Normalized Total Lending (Incl. 0)
Non Interactions(COVID):						
Same Bank	-0.06***	-0.06***	0.47***	-0.08***	-0.03**	-0.14***
	(-8.82)	(-11.02)	(4.06)	(-5.54)	(-2.84)	(-9.24)
Other bank Lenders	0.03*	-0.02***	0.78***	-0.10***		0.04*
	(2.45)	(-4.81)	(5.93)	(-8.03)		(2.47)
Nonbanks	0.01**	-0.01**	1.22***			0.01
	(2.83)	(-2.98)	(8.86)			(1.05)
Interactions:						
Same Bank	-0.05***	0.01**	-0.19*	0.02*	0.03*	-0.10***
	(-5.83)	(2.73)	(-2.36)	(2.34)	(2.14)	(-4.47)
Other bank Lenders	0.02***	-0.00	-0.56***	0.04**		0.05***
	(4.02)	(-0.18)	(-3.48)	(3.02)		(4.49)
Nonbanks	0.06***	0.00	-0.71***			0.11***
	(8.51)	(0.91)	(-5.86)			(8.24)
Time Varying Region Chars	Y	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
δ_b(Prev Lender FE)	Y	Y	Y	Y	Y	Y
δ_g(Lender Type FE)	N	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Observations	141.4MM	6.4MM	5.9MM	1.6MM	2.8MM	139.2MM
Adj R^2	0.47	0.45	0.50	0.47	0.48	0.46

t-statistics are in parentheses

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 14: Credit Cycle And Lending Activity

This table shows estimates of the equation

$$Y_{i,a,t,g} = \sum_{s\,\in \mathcal{G}} \alpha_s 1\{g{=}s\} \times \text{Credit Cycle} + \text{FEs} + \beta \text{Region Chars}_{t-12} + \theta \text{Borrower Chars}_{t-12} + \varepsilon_{i,a,t,g}$$

where t denotes the current period. g is lender type, and $\mathcal{G}$ denotes the set of lender types shown in the first column of the table. a denotes the region the zipcode is located at. The regression is run at the monthly level. Loan Num denotes the number of loans . Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken. Each unit of observation is at the borrower-period-lender type level. Region Chars contains different time-varying regional characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance data is at the monthly level. The credit cycle is derived by scaling credit spread to have a minimum and maximum of -1 and 1. Normalized total lending is equal to total lending(including lending) normalized by the average borrowing of all businesses (including zero borrowing). All variables are winsorized at 0.1% and 99.9% levels.

	Loan Num	Log Loan Am	APR(%)	Log Limit	ΔLog Limit (Existing)	Loan Num	Normalized Total Lending (Incl. 0)
α_s:							
Bank And Credit Unions× Credit Cycle				-0.02**	-0.01*		
				(-2.85)	(-2.12)		
Online× Credit Cycle	-0.04***	-0.02***	1.32***			-0.03***	-0.07***
	(-6.02)	(-3.92)	(8.89)			(-5.37)	(-5.74)
Other Finance× Credit Cycle	-0.03***	-0.02***	0.60***			-0.02***	-0.07***
	(-4.67)	(-4.05)	(4.91)			(-4.21)	(-4.75)
NonFinance× Credit Cycle	0.01	-0.01**	0.05			0.01	-0.01
	(1.89)	(-2.89)	(0.12)			(1.74)	(-0.89)
Time Varying Region Chars	Y	Y	Y	Y	Y	N	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y	N	Y
Time FE	Y	Y	Y	Y	Y	N	Y
Firm FE	Y	Y	Y	Y	Y	N	Y
δ_g(Lender Type FE)	Y	Y	Y	Y	Y	N	Y
$\delta'_g\times$ Time FE	N	N	N	N	N	Y	N
Observations	610.2MM	9.3MM	8.9MM	2.7MM	4.2MM	610.2MM	609.1MM
Adj R^2	0.44	0.43	0.47	0.45	0.44	0.53	0.46

t-statistics are in parentheses
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 15: Borrowing Activity of Non-bank Customers Across Credit Cycles

This table shows estimates of the equation

$$Y_{i,t} = \sum_{s\ \in \mathcal{G}} \alpha_s 1\{g{=}s\} \times \text{Credit Cycle} \times 1(\text{Non-Bank Prev Lender}) + \text{FEs} + \beta \text{Region Chars}_{t-12} + \theta \text{Borrower Chars}_{t-12} + \varepsilon_{i,t}$$

where t denotes the current time. a denotes zipcode. g is lender type and, $\mathcal{G}$ denotes the set of lender types shown in the first column of the table. a denotes the region the business is located at. The regression is run at the monthly level. Loan Num denotes the number of loans . Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken. Each unit of observation is at the borrower-period level. Region Chars contains different time-varying regional characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance data is at the monthly level. The credit cycle is derived by scaling credit spread to have a minimum and maximum of -1 and 1. All variables are winsorized at 0.1% and 99.9% levels.

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	Loan Num	Log Loan Am	APR(%)	Log Employment (12 Month Ahead)	Log Sales (12 Month Ahead)	Norm. Total Lending (Incl. 0)	Lender Change (Conditional On Getting Loan)	Delinquency
Credit Cycle× Non Bank Prev Lender	-0.08***	-0.02**	1.14***	-0.02**	-0.03**	-0.24***	0.23***	0.04**
	(-8.46)	(-3.01)	(7.87)	(-3.22)	(-2.87)	(-8.38)	(5.34)	(3.19)
Time Varying Region Chars	Y	Y	Y	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Prev Lender Type FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	134.1MM	8.8MM	8.3MM	11.3MM	17.5MM	123.6MM	8.4MM	16.4MM
Adj R^2	0.45	0.44	0.49	0.41	0.42	0.46	0.61	0.52

t-statistics are in parentheses
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 16: Credit Cycle and Lending Behaviour of Platform Lenders, Zipcode Level Evidence

This table shows estimates of the equation

$$Y_{a,t,g} = \beta_s 1\{\text{Platform Non Bank}\} \times \text{Credit Cycle} + \text{FEs} + \beta \text{Region Chars}_{t-12} + \varepsilon_{a,t,g}$$

where t denotes the current period. g is lender type, and $\mathcal{G}$ denotes the set of lender types shown in the first column of the table. a denotes the region the zipcode is located at. The regression is run at the monthly level. Loan Num denotes the number of loans . Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken. Each unit of observation is at the zipcode-period-lender type level. Region Chars contains different time-varying regional characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance data is at the monthly level. The credit cycle is derived by scaling credit spread to have a minimum and maximum of -1 and 1. All variables are winsorized at 0.1% and 99.9% levels.

	Log(1+Loan Num)	Log Loan Am	APR(%)
α_s(Bank And Credit Unions as Base):			
Platform Nonbank × Credit Cycle	-0.28***	-0.03***	0.48***
	(-4.07)	(-4.95)	(7.02)
Time Varying Region Chars	Y	Y	Y
δ_g	Y	Y	Y
Time FE	Y	Y	Y
Region FE	Y	Y	Y
Observations	6.3MM	1.8MM	2.2MM
Adj R^2	0.43	0.45	0.46

t-statistics are in parentheses
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 17: Severe Weather Events and Lending Activity

This table shows estimates of equation

$$Y_{i,b,a,t} = \alpha \text{Abnormal Snow}_{t,a} \times \text{Lender Type} + \text{FEs} + \text{Controls} + \varepsilon_{i,b,a,t+\tau} \quad (9)$$

where i denotes firm, b denotes bank,a denotes zipcodes and t denotes time. Abnormal snow indicates whether snow cover is in the top 95% of snow cover of that given zipcode in a given period or not. The data used for determining quantiles is from 1950-2022. Each unit of observation is at the borrower-period-lender type level. Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The dataset contains a large dataset of loans to small businesses provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the quarterly level. All variables are winsorized at 0.1% and 99.9% levels

	Loan Num	Log Loan Am	APR(%)	Log Limit	ΔLog Limit (Existing)	Utilization	Credit Line (Dummy)	Number of Inquiry	Norm. Borrowing (Incl. 0)
Panel A:Same Period Effect									
Big Banks(Top 30)	0.05***	0.02**	0.34*	-0.12**	-0.01	0.15**	0.03		0.13***
	(4.53)	(2.68)	(2.24)	(-2.72)	(-1.91)	(3.23)	(1.92)		(4.57)
Smaller banks and CUs[3]	0.03**	0.04***	0.61***	-0.06*	-0.02*	0.11**	0.02		0.09**
	(3.01)	(4.33)	(3.92)	(-2.11)	(-2.04)	(3.12)	(1.73)		(3.08)
Other Nonbanks	0.02***	0.02**	0.84***						0.05*
	(3.53)	(2.91)	(3.83)						(2.45)
Online Lenders	0.03***	0.02*	1.16***						0.07**
	(3.84)	(2.15)	(4.68)						(2.98)
Panel A1:All Lenders								0.19***	
								(5.87)	
Observations	312.1MM	9.3MM	8.9MM	2.7MM	4.2MM	4.6MM	164.2MM	78.0MM	311.2M
Adj R^2	0.42	0.44	0.45	0.44	0.41	0.45	0.38	0.49	0.43
Panel B: Four Periods(Including Current One)									
Big Banks(Top 30)	0.11***	0.06***	0.42*	-0.08*	-0.01	0.10**	0.09*		0.25***
	(9.48)	(4.84)	(2.43)	(-2.31)	(-1.34)	(2.86)	(2.15)		(5.48)
Smaller banks and CUs[4]	0.08***	0.07***	0.75***	-0.04	-0.01	0.10**	0.06*		0.19***
	(6.45)	(4.79)	(3.98)	(-1.91)	(-1.74)	(2.96)	(2.48)		(4.12)
Other Nonbanks	0.03***	0.02***	0.64***						0.07**
	(4.03)	(4.82)	(4.34)						(3.14)
Online Lenders	0.04***	0.02*	0.86***						0.07***
	(3.92)	(2.23)	(5.05)						(3.56)
Panel B1:All Lenders								0.31***	
								(6.11)	
Observations	286.3MM	8.6MM	8.5MM	2.1MM	3.9MM	3.8MM	143.1MM	71.57MM	285.5MM
Adj R^2	0.40	0.42	0.43	0.42	0.40	0.43	0.36	0.47	0.41
Time Varying Region Chars	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

t-statistics are in parentheses

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Appendices

A Deregulation of Small Banks

This section discusses the consequence of a rule introduced in December 2014 and enacted in May 2015 that helped small banks have less stringent capital regulations. The benefit of analyzing this regulation is that first, it affected a set of lenders at a mass level, and hence, it is easier to analyze the consequences. Second, the effect is positive for the treatment rather than negative, helping us understand whether there is asymmetric effect in substitution between banks and non-banks. This means that it helps us understand whether banks take some customers from non-banks in the event of a positive supply shock. Third, the effect is on the population of smaller banks, which can, in principle, be substituted for nonbanks. The analysis of this section sheds light on the substitution between small banks and nonbanks. Following the financial crisis and the Dodd-Frank Act of 2010, regulations on small banks were tightened. On the other hand, it is well documented that it is difficult for small businesses to access capital, and lending to them is crucial for survival. Following the 2008 financial crisis, several regulatory agencies increased capital requirements for various players in the banking industry. The majority of stricter regulatory standards are implemented through tougher bank regulations. Capital requirements are designed to reduce the systemic risk of the financial system, which materialized in the financial crisis. Small businesses may be harmed by stricter rules, which could prevent small banks from originating enough loans.

As a result of the "Small Bank Holding Company (SBHC) Policy Statement," which took effect in May 2015 and was enacted into law in December 2014, the definition of a small bank holding company has changed. With the small BHC status, various capital requirements have been withdrawn, resulting in overburdening small BHCs and less restrictive capital regulation at the parent holding company level. BHCs are regulated differently depending on their size, with "small BHCs" being treated more kindly. Basel III exempts newly recognized small BHCs from risk-based and leverage capital requirements. A BHC will now have an asset threshold of $1 billion instead of $500 million to qualify as a small entity under the regulatory change. As a result of these exemptions, small BHCs can carry more debt. Above the asset threshold of $1 billion, BHCs are restricted in terms of how much debt they can hold, and any debt issued is qualified as Tier-2 capital only under restricted conditions. Under the SBHC Policy Statement, BHCs regulated as small entities can inject Tier-1 capital through increased debt capacity. At the end of 2022, 3920 bank holding companies were subject to different levels of regulation in the U.S. banking system, which construes most of the banking system. Generally, a tailored regulatory approach recognizes the importance of small banks for the economy and offers financial flexibility to small BHCs.

I apply a difference-difference approach to compare banks' lending activities eligible for relaxed capital requirements since implementing the policy to all other lenders that haven't been treated. In the untreated group, all banks within a holding company are unaffected by the regulatory change. All credit unions are included in the control group, in addition to nonbanks. Additionally, I examine how regulatory changes are affecting the economy. Increasing small business lending can benefit the US economy because small businesses are a key driver of economic growth(Haltiwanger (2022),Haltiwanger and Krizan (1999),Davis, Haltiwanger, and Schuh (1996)). To determine whether this reasoning is supported empirically, a detailed analysis of the firms' outcomes was conducted. The regulatory change has a slight positive and significant effect on real employment in the short run because firms that receive loans from treatment banks perform better than those from control banks. It is possible that true treatment firms would not have received funding if relaxation hadn't taken place. However, the number of delinquencies appears to increase in the year after gradually.

Small bank holding companies that become qualified are also subject to enhancements and regulation changes. As a result of a reduction in parent company reporting volumes, the additional modifications are unlikely to impact lending activity negatively. For example, the number of items reported in call reports has been reduced for small bank holding companies.

The existing literature explores some themes that are in line with my research. These include: Chen, Lu, and Wang (2017) ,Buchak et al. (2018),Gropp et al. (2019),Granja, Leuz, and Rajan (2022),Cortés et al. (2020), the initial theme examines the consequences of variations in regulatory burden among various lenders on their lending activities. As an example, Buchak et al. (2018) illustrates how heightened regulatory demands may reduce mortgage lending by traditional banks while increasing lending activities by shadow banks and FinTech lenders. Regulatory measures applied to the banking sector have reduced conventional bank lending, which aligns with the perspective that regulatory measures have reduced bank lending. According to Cortés et al. (2020) and Chen, Lu, and Wang (2017), regulatory limitations placed on larger banks may have adverse effects, particularly on their lending activities. This paper aims to contribute to this literature by discussing how reducing regulation might benefit small businesses. Additionally, there is literature regarding the impact of small banks on the economy (Degryse and Van Cayseele (2000), Behr, Norden, and Noth (2013), Cortés (2014), Berger and Bouwman (2017)). Studies have consistently shown that smaller banks can better alleviate the financial constraints of small and medium-sized businesses (SMBs). To achieve this, they cultivate strong relationships, know their clients intimately, and pay attention to soft information. Studies such as Berger and Bouwman (2017) highlight certain drawbacks associated with the potential disappearance of small banks. As a result of my analysis, reducing excessive regulatory restrictions on small bank holding companies would negatively impact the economy by hindering small business lending. My analysis centers around 2014, 2015, and the subsequent two years. December 2014 marked the effective date of the SBHC Policy, which became effective in May 2015.

The regulatory classification of a Bank Holding Company has been modified due to this regulatory adjustment. In particular, it raises the asset threshold for categorizing Bank Holding Companies as small entities from \$500 million to \$1 billion. Specifically, Basel III exempts newly recognized small Bank Holding Companies from risk-based and leverage capital regulations. Because of these exemptions, bank-holding companies can issue risky loans and increase their debt. The recent regulation limits the debt and lending operations permitted for Bank Holding Companies with assets exceeding \$1 billion. Consequently, the SBHC Policy Statement allows Bank Holding Companies to strengthen their Tier-1 capital and facilitate credit extension through expanded debt capacity. By adjusting capital regulations, the SBHC Policy Statement supports local economic growth, enhances small business resilience, and makes credit more accessible to small businesses.

Table 18 shows the effect of small bank regulation on lending by different entities. The results use the following regression:

$$Y_{i,g,b,t} = \sum_{j} \alpha_j 1\{j{=}g\} \times \text{POST}_t + \text{FEs} + \beta\text{Region Chars}_{t-1} + \theta\text{Borrower Chars} + \varepsilon_{i,b,t} \quad (10)$$

The equation is run yearly and contains the years 2014 and 2015. b denotes bank type,i denotes firm and t denotes time and g is previous lender type. Using a difference-in-difference setting, the regression analyzes loan supply by lenders depending on whether they had a previous relationship with the treatment banks. The first column determines whether lending has increased to businesses with prior relationships with a lender by the same lender or not. The second column shows the result for lending by all lenders. The treated banks partly steal loans from other small and non-banks but do not steal customers from larger banks. Due to this, there may be implications for estimating the substitution between different lenders. It appears that SMB loans are partially segmented, with smaller lenders matching with certain types of borrowers and not competing heavily with bigger banks. The two other columns show that for the sample of firms with past relationships to different lender types, getting a loan from a treated bank leads to an increase in the loan amount and a decrease in APR.

Table 19 shows employment and sales outcomes results. The results are for the regression of real outcomes on whether a business has gotten a loan. Getting a loan is instrumented by whether the business has had past relationships with a treated bank, and hence, the following equation is used:

$$Y_{i,b,t} = \alpha\text{Loan}_{b,t} + \text{FEs} + \beta\text{Region Chars}_{t-1} + \theta\text{Borrower Chars} + \varepsilon_{i,b,t} \quad (11)$$

The results are shown in table 19. There seems to be a minor improvement in sales, employment, and delinquency in the current year, but the effect diminishes in the year after, and actually, delinquency increases in the following year. This might mean that the increased supply of smaller banks might go to risky firms on the brink of getting delinquent on their loans. If this is the case, the deregulation might have had mixed positive outcomes.

Overall, this section presents suggestive evidence on the substitutability of small banks with nonbanks and also casts doubt on the benefits of deregulation of small banks. This can posit the question of whether nonbanks should still be held unregulated or not. The finding of this section might hint that small banks and non-banks are similar in terms of their lending activity.

Table 18: Effect of Small Bank Deregulation on Loan Characteristics Depending on Previous Lender Type

The columns 1,4,5 of the table shows estimates of equation

$$Y_{i,g,b,t} = \sum_j \alpha_j 1\{j{=}g\} \times \mathrm{POST}_t + \mathrm{FEs} + \beta \mathrm{Region\ Chars}_{t-1} + \theta \mathrm{Borrower\ Chars} + \varepsilon_{i,b,t}$$

where b denotes bank, i denotes firm and t denotes time and g is the previous lender type. The regression is for years 2014 and 2015 and is run at the yearly level. Each unit of observation is at the borrower-period-bank level. Treated Banks are the control group in this regression. The column 2 and 3 compare the loan amount and APR of different types of lenders to treated banks using the following equation:

$$Y_{i,g,b,t} = \sum_j \alpha_j 1\{j{=}g\} \times \mathrm{POST}_t + \mathrm{FEs} + \beta \mathrm{Region\ Chars}_{t-1} + \theta \mathrm{Borrower\ Chars} + \varepsilon_{i,b,t}$$

where g is (current) lender type and the rest is the same as previous equation. Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The dataset contains FDIC SOD and Event and Changes in Bank Suite and the large dataset of loans to small businesses provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels

	Loan Num (Own)	Log Loan Am (Total)	APR(%) (Total)	Loan Num (Total)	Loan Num (Treated)
Bigger Lenders	-0.13***	-0.06***	0.33*	-0.08***	-0.08***
	(-3.95)	(-3.64)	(2.52)	(-3.42)	(-4.95)
Smaller banks and credit unions	-0.14***	-0.07**	0.34*	-0.07***	-0.06***
	(-3.55)	(-3.11)	(2.48)	(-3.33)	(-3.61)
Nonbanks	-0.16***	-0.05**	0.23*	-0.08**	-0.05**
	(-4.78)	(-2.85)	(2.36)	(-3.05)	(-2.70)
Online Lenders	-0.15***	-0.04*	0.26*	-0.06**	-0.05**
	(-4.16)	(-2.50)	(2.48)	(-2.75)	(-2.80)
R^2	0.43	0.45	0.47	0.44	0.42
Panel B:					
Treated Banks	0.14***	0.05***	-0.29***	0.07***	0.06***
	(8.47)	(6.48)	(-3.56)	(5.42)	(6.85)
R^2	0.40	0.42	0.45	0.42	0.40
Time Varying Region Chars	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y
δ_g(Lender Type FE)	Y	Y	Y	Y	Y
Observations	6.3MM	4.8MM	4.7MM	6.3MM	6.3MM

t-statistics are in parentheses
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 19: Real Effects of Small Bank Deregulation for Firms with A Prior Relationship to At Least One Bank,Second Stage Result

This table shows estimates of equation

$$Y_{i,b,t} = \alpha \text{Loan}_{b,t} + \text{FEs} + \beta \text{Region Chars}_{t-1} + \theta \text{Borrower Chars} + \varepsilon_{i,b,t}$$

where b denotes bank, i denotes firm and t denotes time. The regression is for years 2014 and 2015 and is run at the yearly level. Each unit of observation is at the borrower-period-bank level. Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The dataset contains FDIC SOD and Event and Changes in Bank Suite and the large dataset of loans to small businesses provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels

	Current Year			Next Year		
	Log Employment	Log Sales	Delinquency	Log Employment	Log Sales	Delinquency
Loan Num	0.02**	0.03*	-0.05*	0.00	-0.01	0.02*
	(3.14)	(2.52)	(-2.53)	(0.14)	(-1.81)	(2.37)
Demeaned Region Chars	Y	Y	Y	Y	Y	Y
Firm× Time FE	N	N	N	N	N	N
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	N	N	N	N	N	N
Lender FE	N	N	N	N	N	N
Observations	3.7MM	5.4MM	5.6MM	3.5MM	5.3MM	5.4MM
R^2	0.43	0.41	0.42	0.41	0.40	0.39

t-statistics are in parentheses
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

B Other Figures

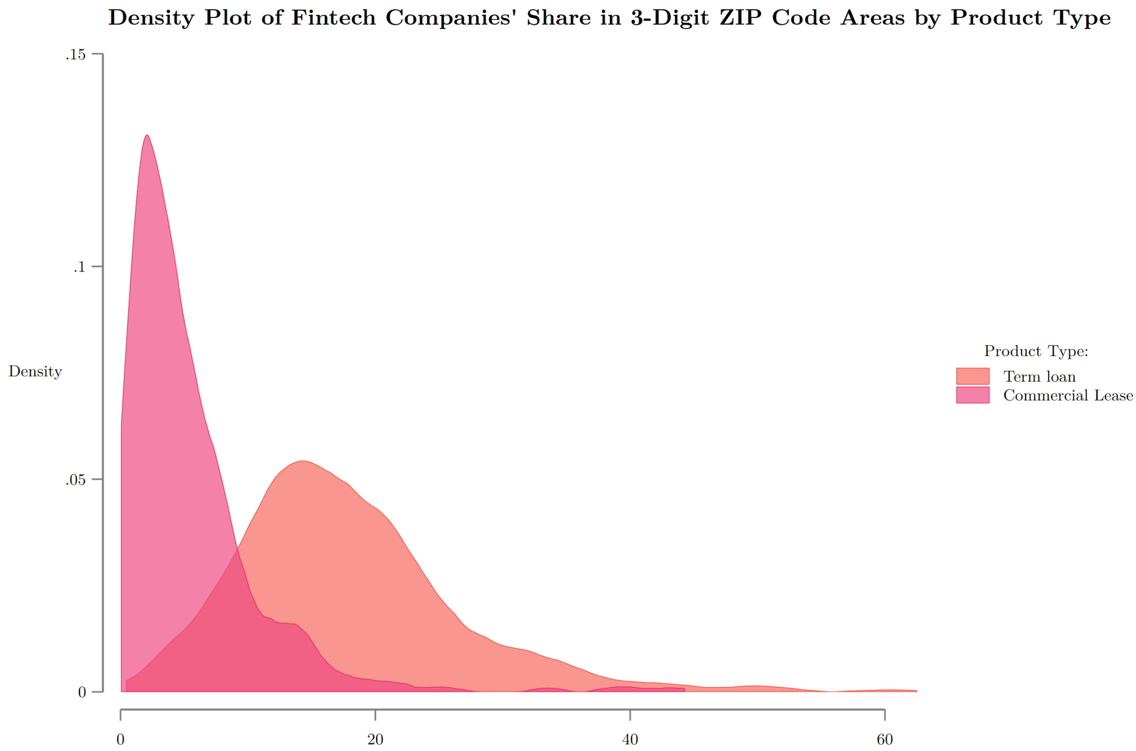

Figure 15: This figure provides kernel density of market share of online lender Companies in 3-Digit Zip Code Areas for different financial product markets. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

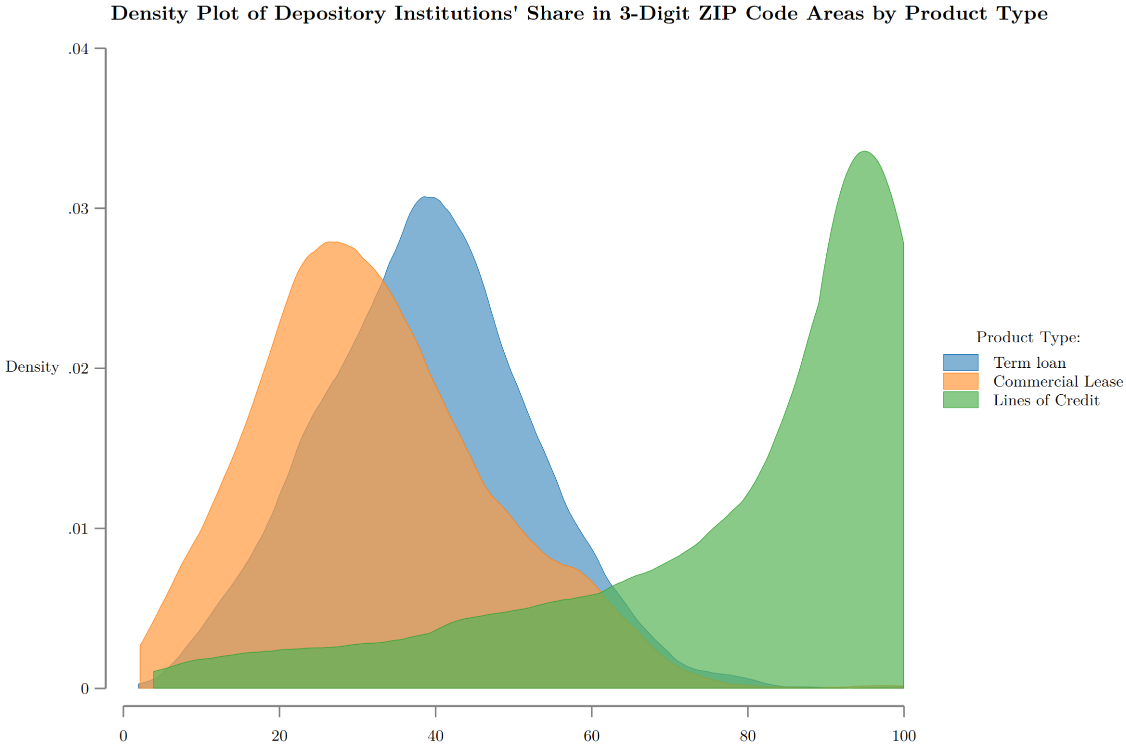

Figure 16: This figure provides kernel density of market share of Depository Institutions in 3-Digit Zip Code Areas for different financial product markets. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

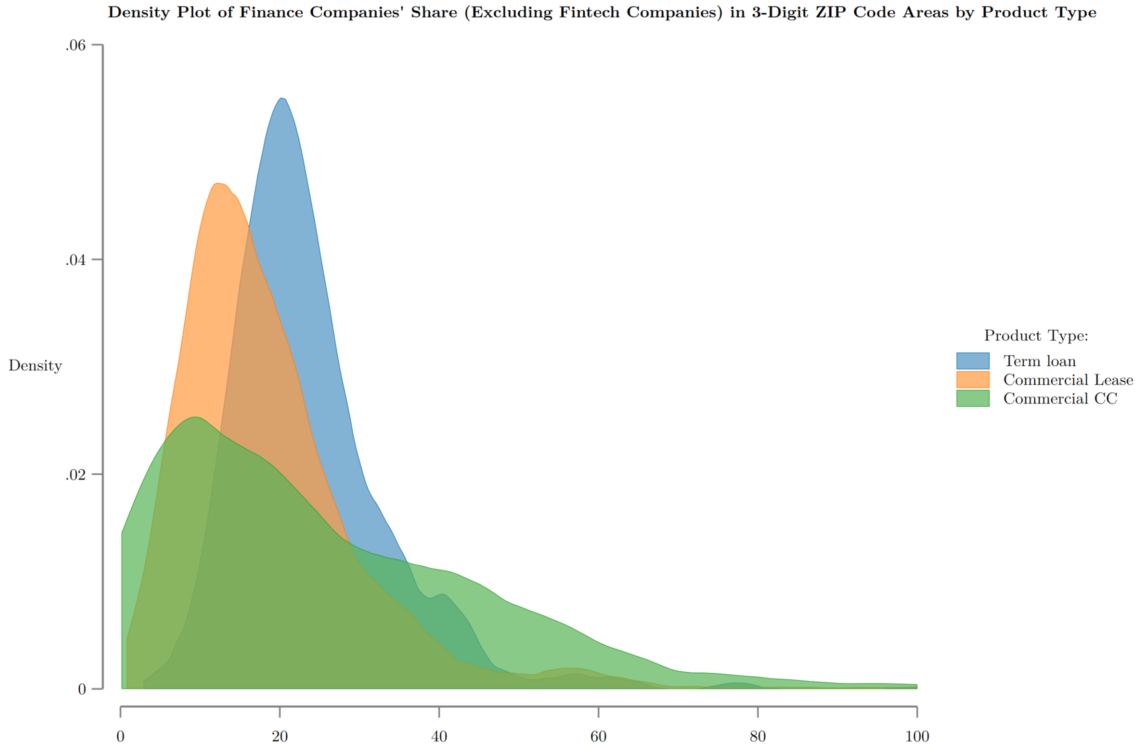

Figure 17: This figure provides kernel density of market share of Finance Companies(Excluding Fintech) in 3-Digit Zip Code Areas for different financial product markets. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

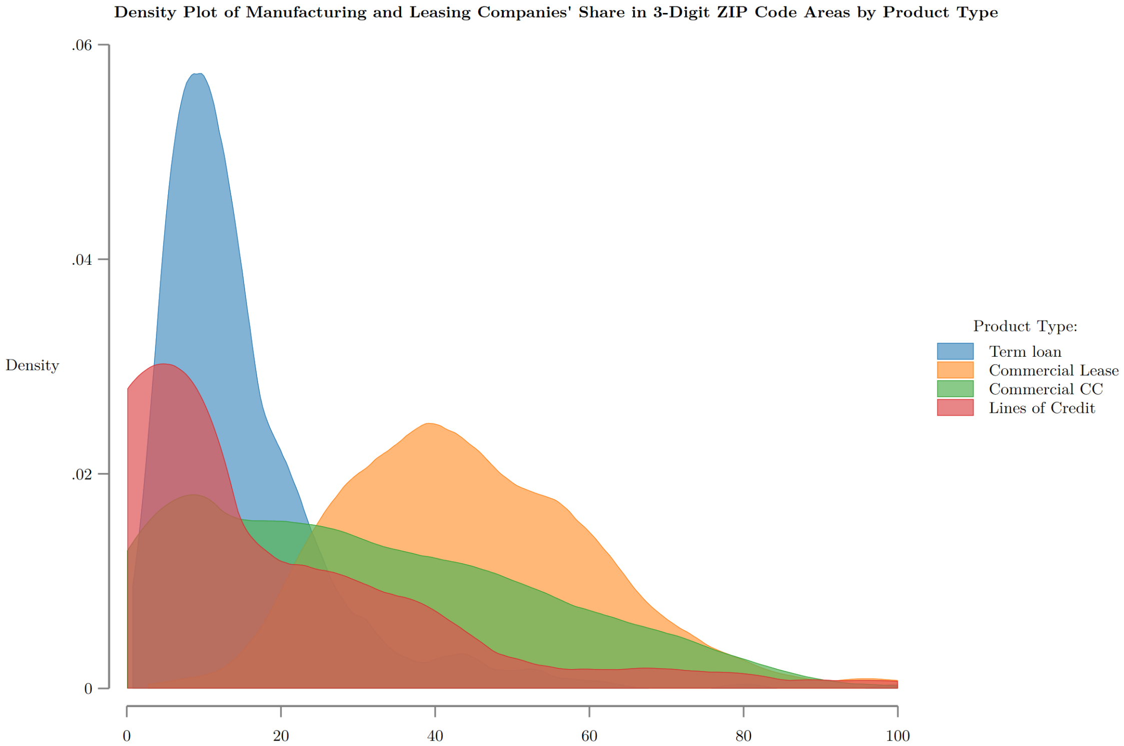

Figure 18: This figure provides kernel density of market share of Manufacturies/Leasing Companies in 3-Digit Zip Code Areas for different financial product markets. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

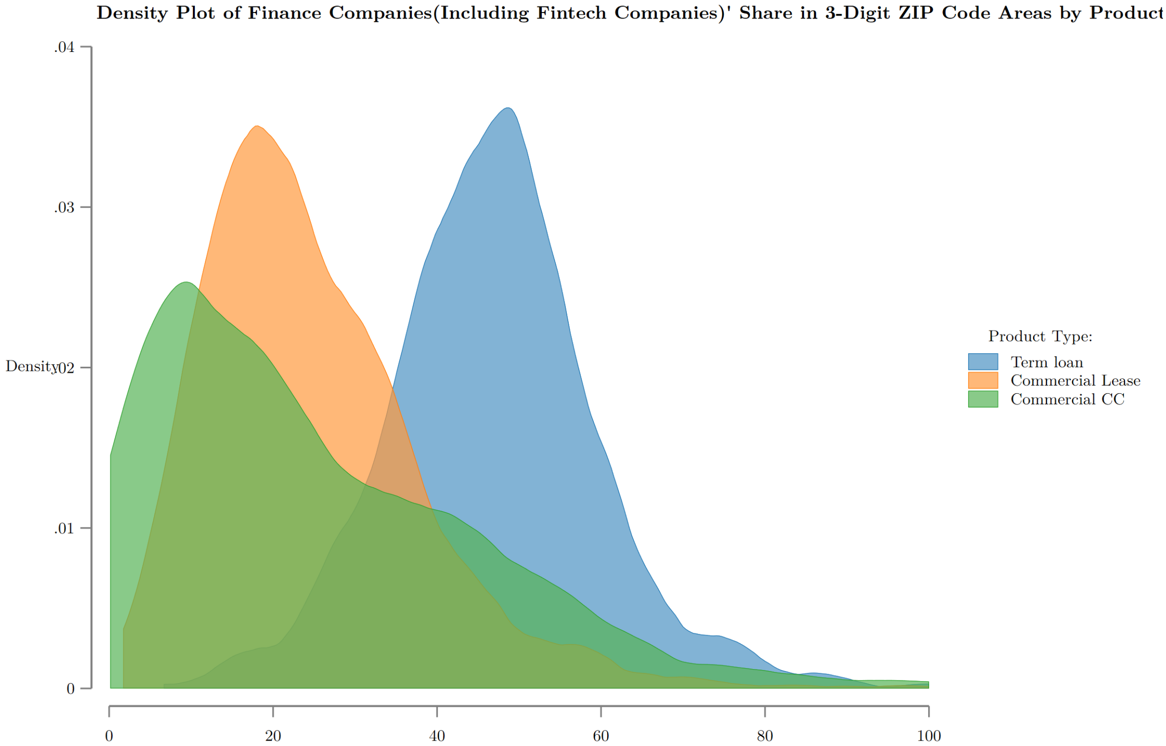

Figure 19: This figure provides kernel density of market share of Finance Companies(Including Fintech) in 3-Digit Zip Code Areas for different financial product markets. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

Number of Loans Between Different Partitions of Data

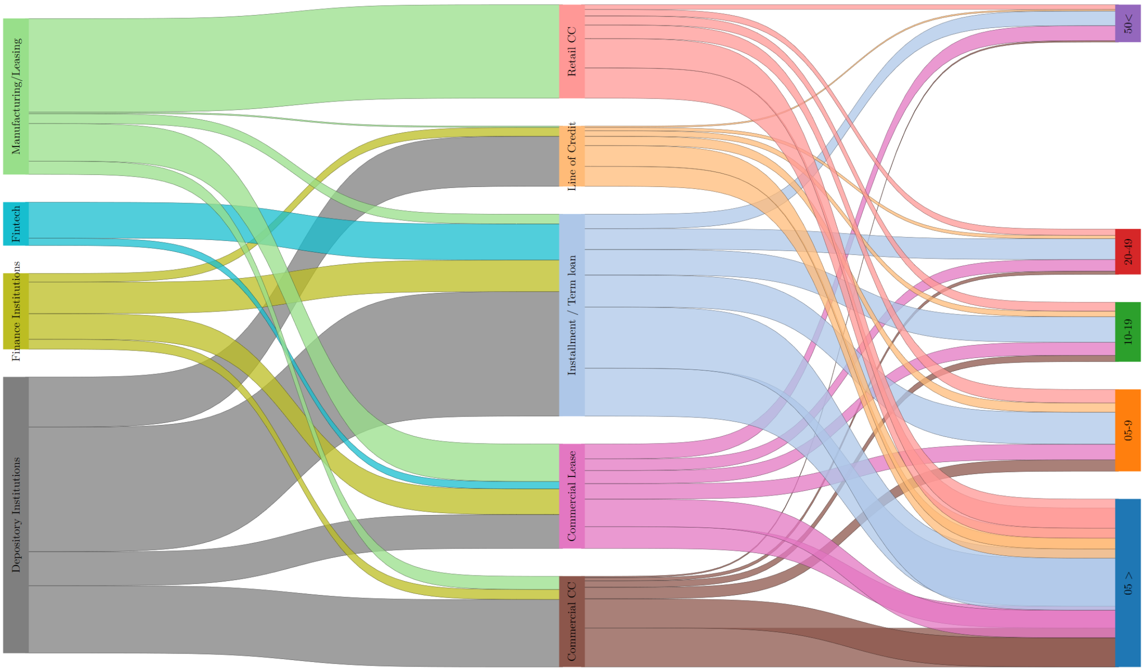

Figure 20: This figure provides Sankey graph of lending between different partitions of data. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

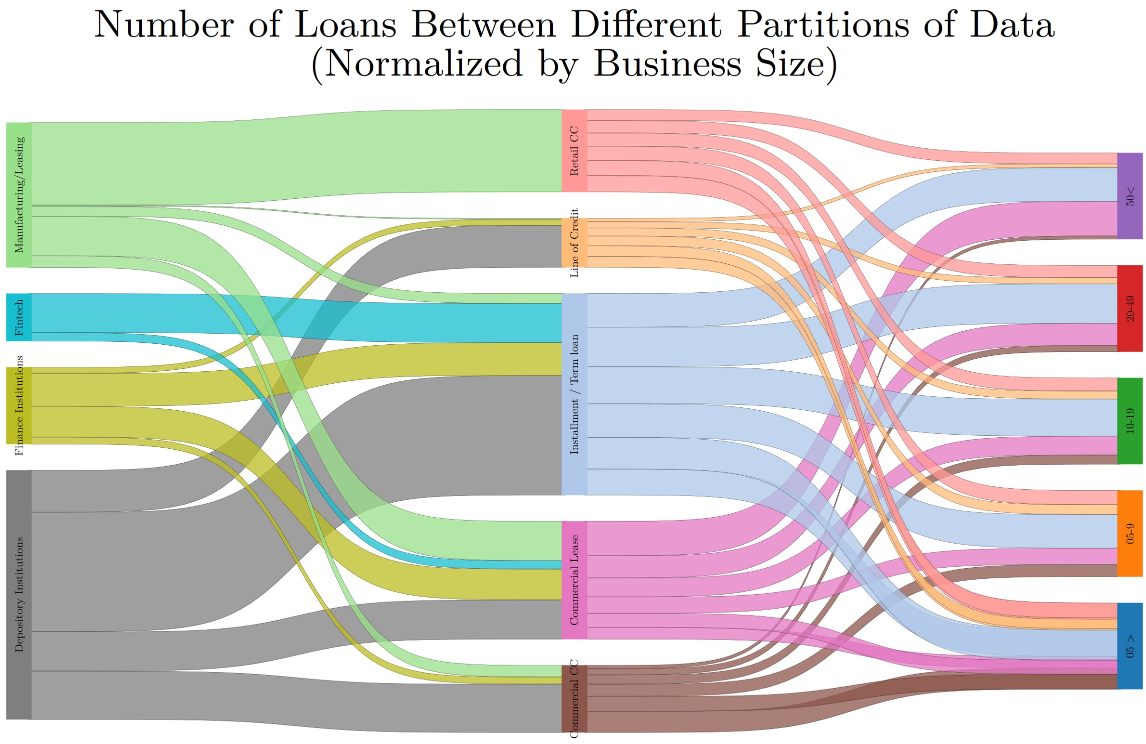

Figure 21: This figure provides a Sankey graph of lending between different partitions of data where it is normalized by the business size category. As a result, each business will have the same size. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

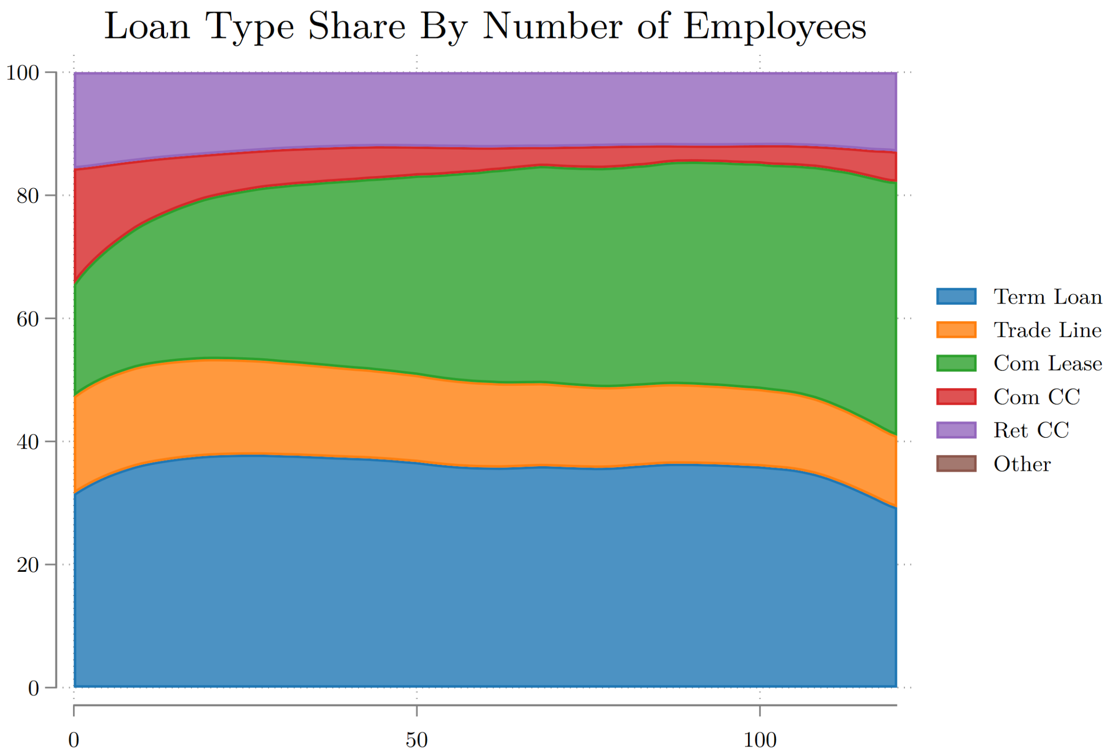

Figure 22: This figure provides a distributional graph of loan type by number of employees. As a result, each business will have the same size. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

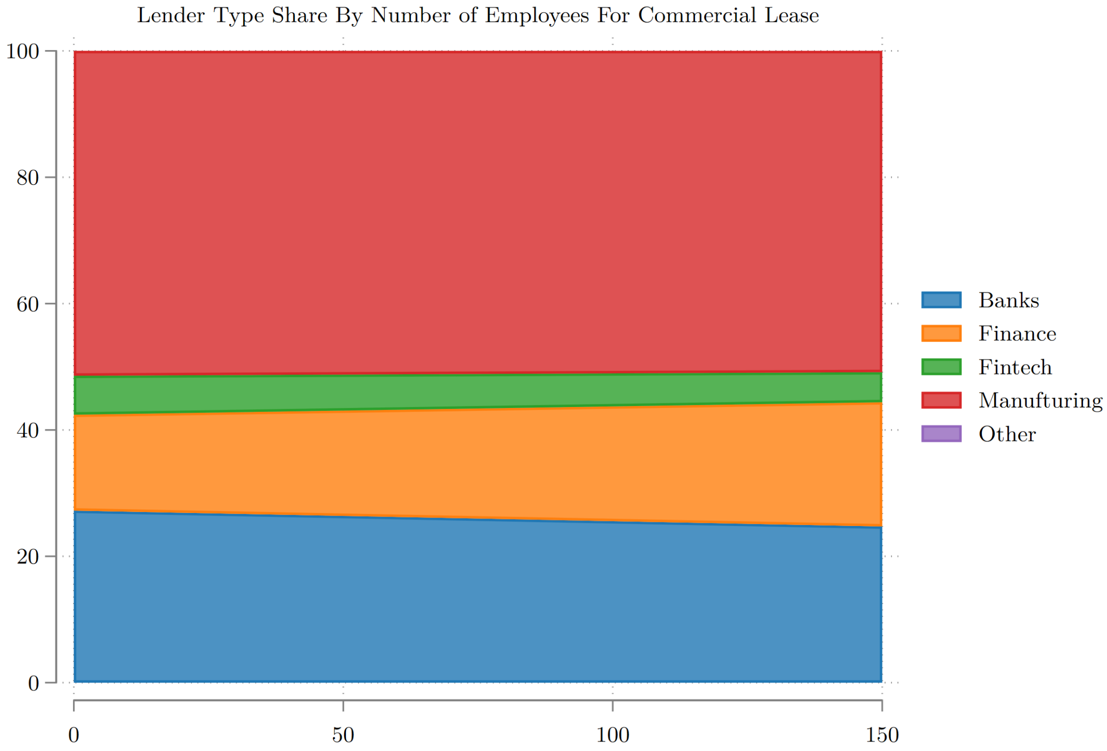

Figure 23: This figure provides a distributional graph of lender type by number of employees for commercial lease. As a result, each business will have the same size. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

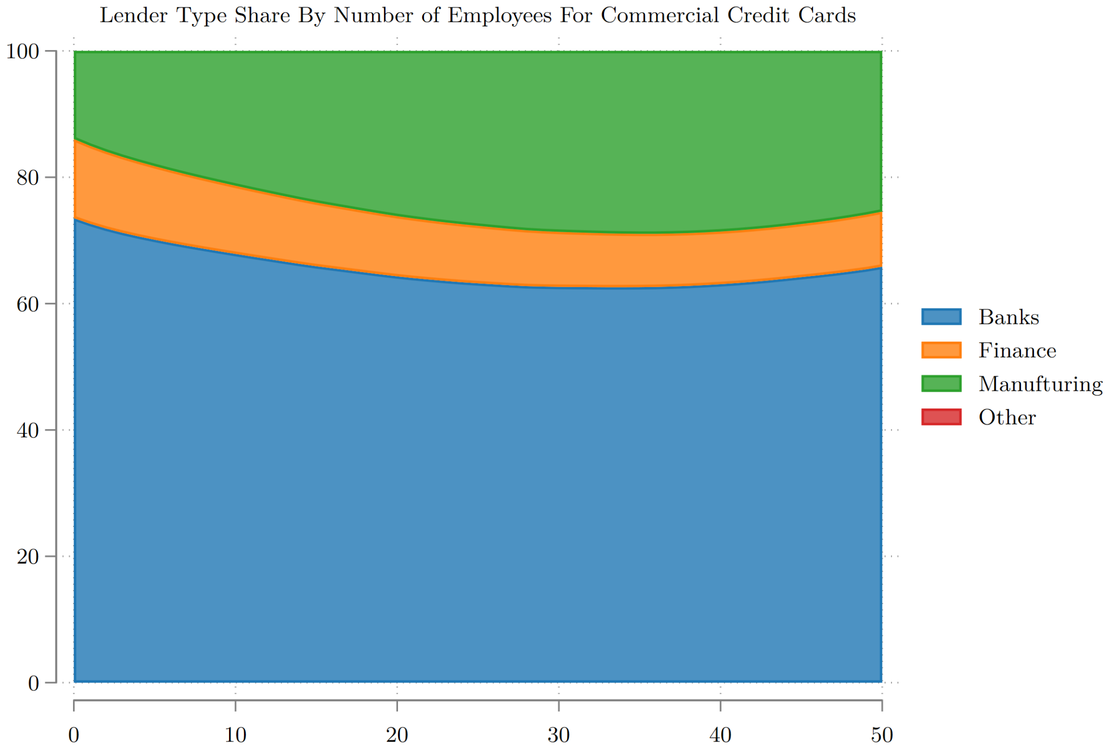

Figure 24: This figure provides a distributional graph of lender type by number of employees for commercial credit card. As a result, each business will have the same size. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

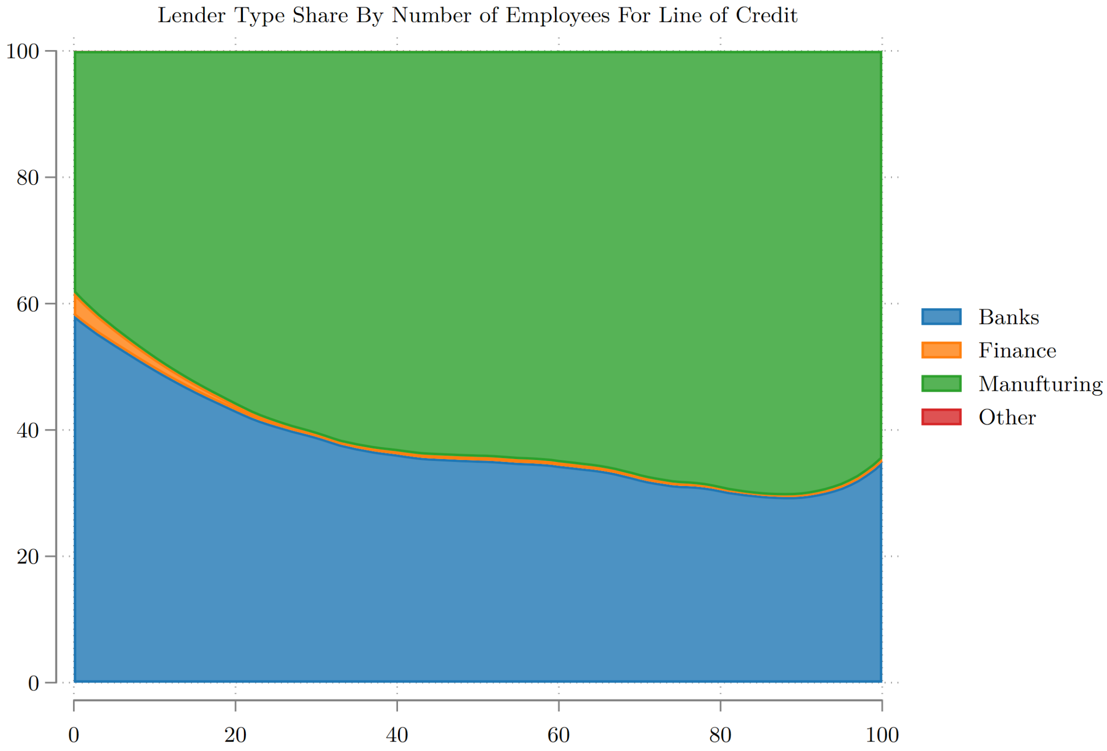

Figure 25: This figure provides a distributional graph of lender type by number of employees for Line of Credit. As a result, each business will have the same size. The data is from one of the credit bureaus. The data covers periods 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels. A bank/Credit Union is defined as any lender with depository institution status. An online lender is any finance company that operates online and does not have a branch presence.

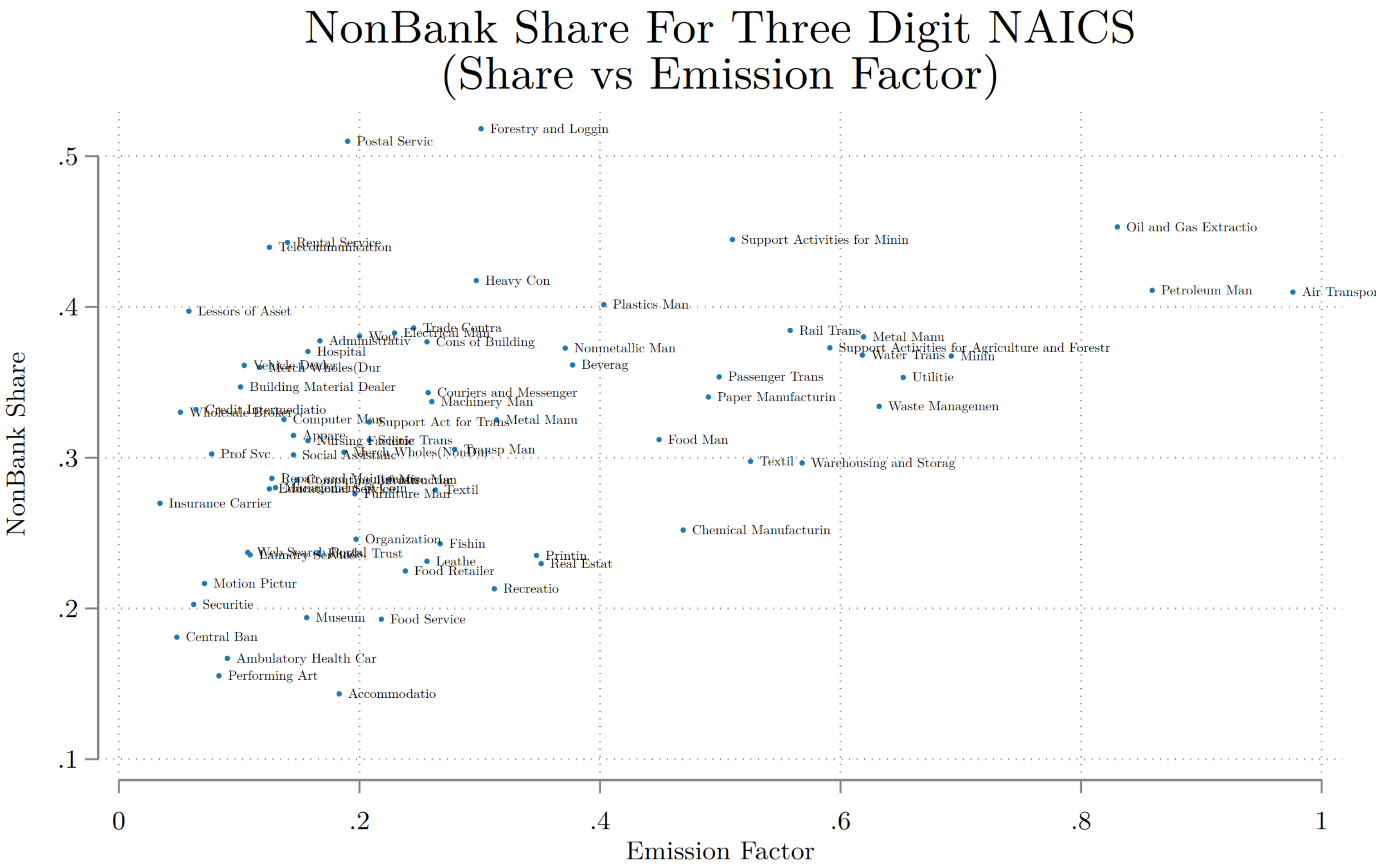

Figure 26: This figure depicts nonbank Share across three-digit industries versus emission factor. The nonbank Share is using author's calculation using data from 2014 to 2022. emission factor is from supply chain greenhouse gas emission factors v1.2 by NAICS-6 from U.S. Environmental Protection Agency. The emission factor is supply chain emission factors with margins.

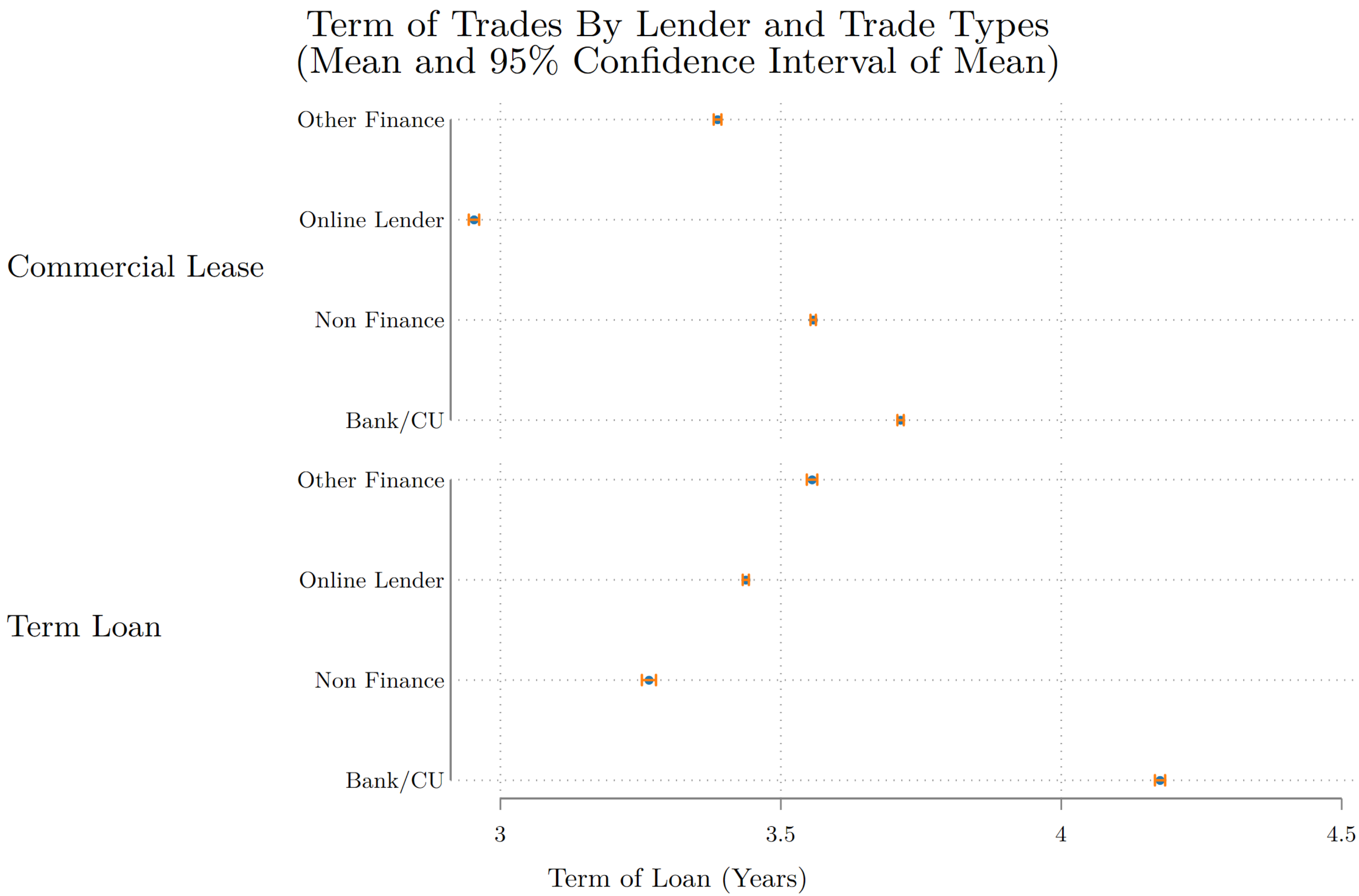

Figure 27: This figure depicts the Term of Trades by Lender-Type and lender type. Term of trade is the number of years till the the loan or lease is paid off. The data is from the main dataset for years 2014 to 2022.

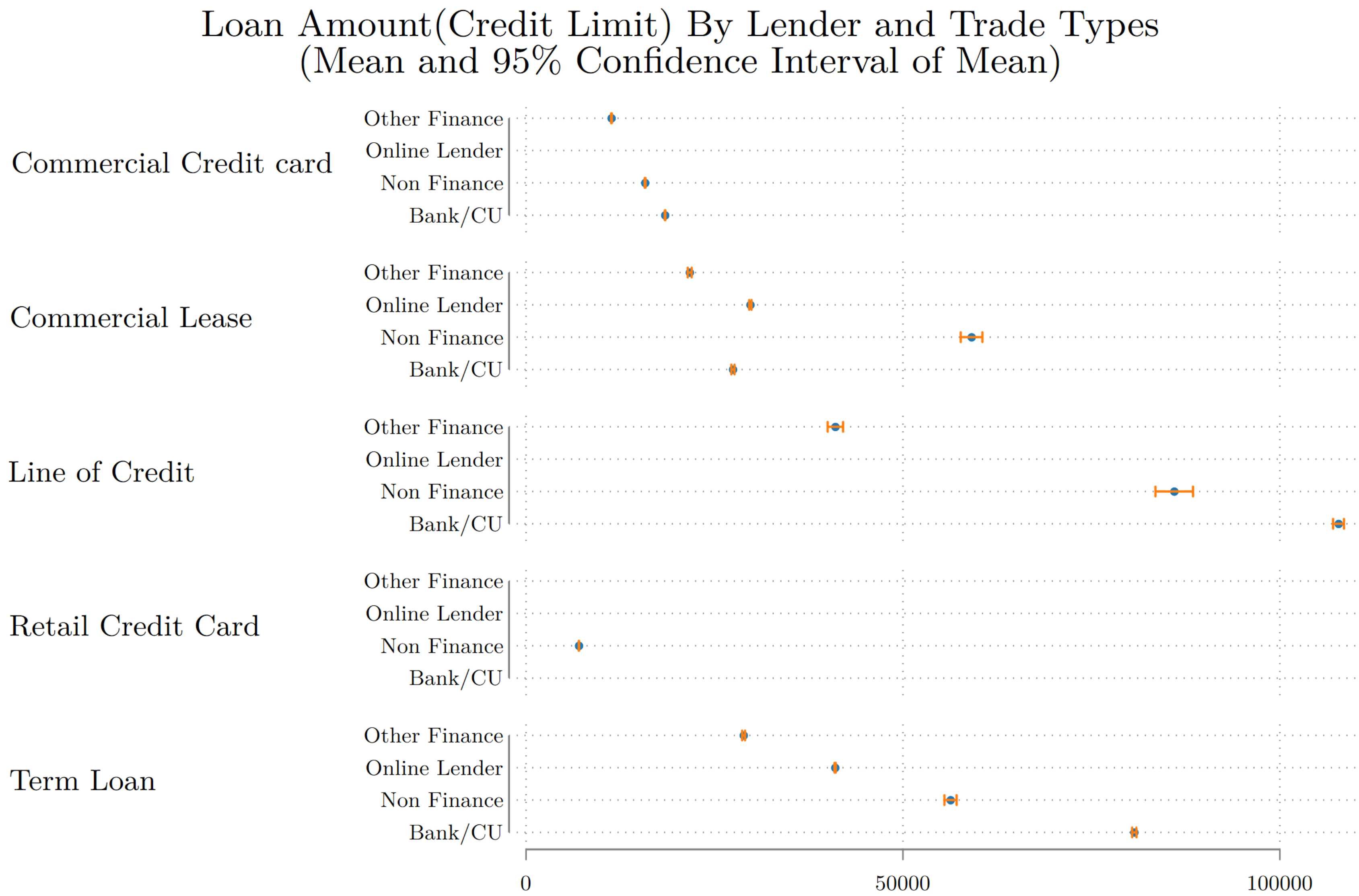

Figure 28: This figure depicts the Loan Amount/Credit Limit by Lender-Type and lender type. Loan Amount/Credit Limit is in USD. The data is from the main dataset for years 2014 to 2022.

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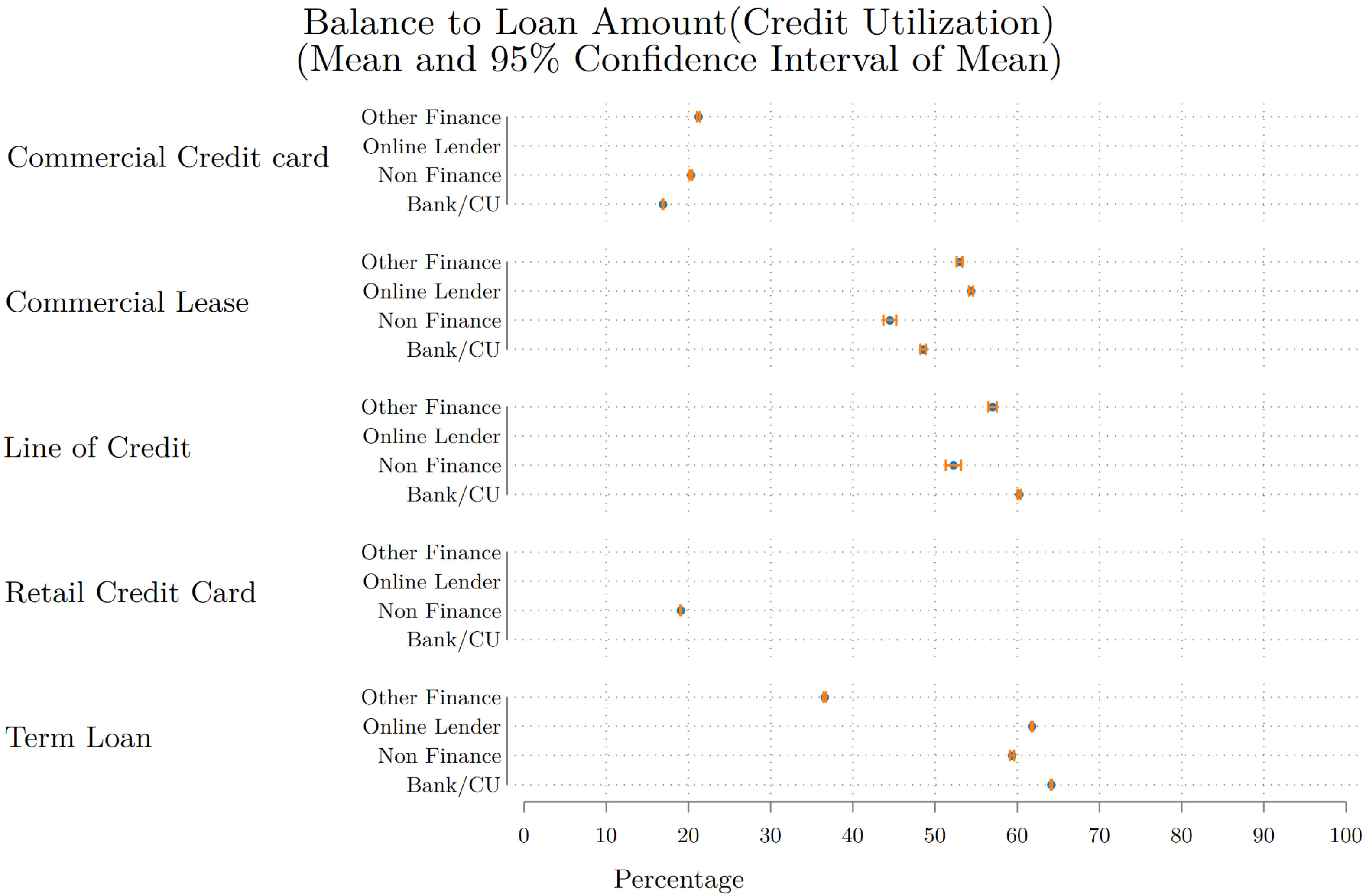

Figure 29: This figure depicts the utilization ratio (balance to loan amount) by lender-type and lender type. Utilization ratio is percentage of balance to credit limit or loan amount. The data is from the main dataset for years 2014 to 2022.

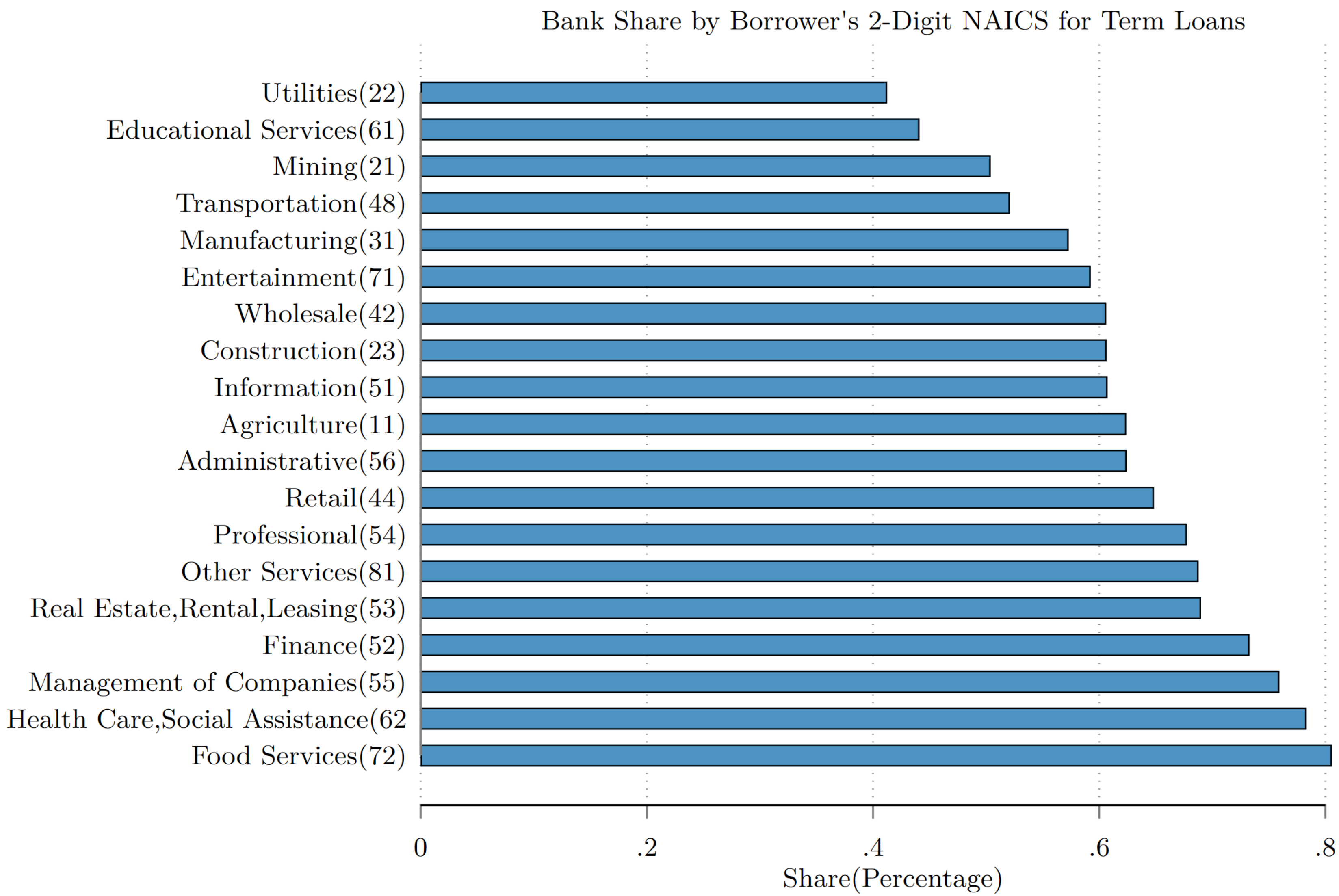

Figure 30: Bank Share by Borrower's 2-Digit Naics for Term Loans. The data is from the main dataset for years 2014 to 2022.

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C Other Tables

Table 20: Effect of Bank Closing on Other Products Issued

This table shows estimates of equation

$$Y_{i,b,a,t,g} = \sum_{s \in \mathcal{G}} \alpha_s \text{Closed}_{b,t,a} \times 1\{g = s\} + \text{FEs} + \beta \text{Region Chars}_{t-12} + \theta \text{Borrower Chars}_{t-12} + \varepsilon_{i,b,a,t,g}$$

t denotes the current time. a denotes zipcode and b is bank. g is lender type and $\mathcal{G} = \{\text{Same Lender,Other banks,Nonbank}\}$ is the set of lender types. For brevity, only the coefficient on the same lender is reported. The regression is run at the monthly level. Loan Num denotes the number of loans given in the last 12 months. Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken in the past twelve months. Each unit of observation is at the borrower-period-previous lender-lender type level. The regressions are IVed by the 12-month lag of the Exposure variable. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The dataset contains FDIC SOD and Event and Changes in Bank Suite and the large dataset of loans to small businesses provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels.

	Commercial Lease	Commercial Credit Card	Number of Inquiries
α			
Same Lender	-0.01	0.00	
	(-1.02)	(0.15)	
Other Bank lenders	0.00	-0.00	
	(0.09)	(-0.19)	
Nonbanks	0.01	0.00	
	(0.82)	(0.24)	
Any Lender			0.03**
			(3.14)
Time Varying Region Chars	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y
Firm FE	Y	Y	Y
δ_b(Prev Lender FE)	Y	Y	Y
δ_g(Lender Type FE)	Y	Y	Y
Time FE	Y	Y	Y
Observations	202.3MM	198.1MM	69.7MM
Adj R^2	0.43	0.41	0.39

t-statistics are in parentheses
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 21: Bank Closing and Lending Activity for Firm-Lender Pairs with No Relationship, Top 20 Lenders in Each Zipcode

This table shows estimates of equation

$$Y_{i,b,a,t} = \alpha \text{Closed}_{b,t,a} + \text{FEs} + \beta \text{Region Chars}_{t-12} + \theta \text{Borrower Chars}_{t-12} + \varepsilon_{i,b,a,t}$$

where t denotes the current time. i denotes the firm. a denotes zipcode. g is lender type. a denotes the region the business is located at. b is bank(previous lender). The regression is run at the monthly level. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Loan Num denotes the number of loans given in the last 12 months. Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken in the past twelve months. Closed denotes the cumulative number of closings relative to time $t-12$. Each unit of observation is at the borrower-period-previous lender-lender type level. The regressions are IVed by the 12-month lag of the Exposure variable. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Region Chars contains different time-varying regional characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance data is at the monthly level. All variables are winsorized at 0.1% and 99.9% levels

	Loan Num	Log Loan Am	APR(%)	Log Limit	Normalized Total Lending (Incl. 0)
Same Lender	-0.00	-0.02*	0.28	-0.03*	-0.02*
	(-0.08)	(-2.45)	(1.91)	(-2.04)	(-2.14)
Time Varying Region Chars	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
δ_b(Prev Lender FE)	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y
Observations	1.3B	2.8MM	2.6MM	782.1K	1.3B
Adj R^2	0.41	0.43	0.44	0.42	0.42

t-statistics are in parentheses
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 22: Lending Across Credit Cycles: Zip code Level Evidence

This table shows estimates of equation

$$Y_{b,a,t,g} = \sum_{s\, \in \mathcal{G}} \beta_s \text{Closed}_{b,t,a} \times 1\{g = s\} \times \text{Credit Cycle} + \sum_{s\, \in \mathcal{G}} \alpha_s \text{Closed}_{b,t,a} \times 1\{g{=}s\} + \text{FEs} + \beta \text{Region Chars}_{t-1} + \theta \text{Borrower Chars}_{t-1} + \varepsilon_{b,a,t,g} \tag{12}$$

t denotes the current time. a denotes zipcode and b is bank. Loan Num denotes the number of loans given in the last 12 months. Loan Am(Amount), APR, and Limit are the average loan amount, APR, and limit for loans taken in the past twelve months. The regressions are IVed by the 12-month lag of the Exposure variable. Exposure is a dummy variable that is equal to one if both target or acquirer have at least one branch in the zip code. Each unit of observation is at the zipcode-period-previous lender-lender type level. Region Chars contains different time-varying region characteristics, including population, percentage Hispanic or African-American, percentage single, percentage employed, percentage college educated, and per capita income. Time-varying Borrower characteristics include age, number of employees, annual sales, and number of bankruptcy filings. The dataset contains FDIC SOD and Event and Changes in Bank Suite and the large dataset of loans to small businesses provided by one of the credit bureaus. The data covers the period 2014 through 2022. Business level characteristics are provided at the yearly level, and loan performance is at the monthly level. The credit cycle is derived by scaling credit spread to have a minimum and maximum of -1 and 1. All variables are winsorized at 0.1% and 99.9% levels

	Loan Num	Log Loan Am	APR(%)	Log Limit	Normalized Total Lending (Incl. 0)
β_s:					
Same Lender× Credit Cycle	0.00	-0.02*	0.07	-0.04*	-0.02*
	(1.34)	(-1.98)	(1.13)	(-2.31)	(2.42)
Other Bank lenders× Credit Cycle	-0.01*	-0.02*	0.37*	-0.04**	-0.04**
	(-2.09)	(-2.29)	(2.11)	(-2.67)	(-3.08)
Nonbanks× Credit Cycle	-0.04***	-0.02*	0.47**		-0.09***
	(-4.04)	(-2.49)	(3.02)		(-4.01)
Time Varying Region Chars	Y	Y	Y	Y	Y
Time Varying Borrower Chars	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
δ_b(Prev Lender FE)	Y	Y	Y	Y	Y
δ_g(Lender Type FE)	Y	Y	Y	Y	Y
Observations	8.3MM	2.9MM	2.7MM	974.8K	8.2MM
Adj R^2	0.45	0.47	0.48	0.46	0.48

t-statistics are in parentheses
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$