Small Business Lending and the Bank-Branch Network

Ivan Petkov *

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Abstract

I examine the role of bank's distance to the borrower and the proximity of other lenders for the transmission of financial shocks across the bank network. I use a novel dataset of small business lending based on information from the Community Reinvestment Act, which measures lending at census tract groups *within* each county and yields rich variation in the bank-borrower and borrower-competitor distance. I document that small banks with increased liquidity from proximity to local oil booms, originate more loans to firms far from these booms, and lenders with above-average geographic exposure to residential booms reduce lending in census tract groups with stable house prices. Bank-borrower distance is important for credit expansions, with closer firms receiving more credit, but not for contractions. Proximity of competitors plays a key role: consistent with theoretical predictions, both credit expansions and contractions disproportionately affect markets where the bank faces higher competition.

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*Author's affiliation: Northeastern University; email: i.petkov@neu.edu; tel:857-869-5353. Present address: Department of Economics, Northeastern University, 360 Huntington Ave, Boston, MA 02115; Declarations of interest: none. I am grateful to Susanto Basu, Francesco Giavazzi, Adam Guren, Pierre De Leo, Jun Ma, Filippo De Marco, and other seminar participants at Boston College, Boston University, and the Boston Federal Reserve Bank. Special thanks go to Fabio Schiantarelli, Philip Strahan, and Scott Fullford for their guidance and advice.

1 Introduction

Multi-market banks improve capital mobility and resource allocation in local markets.[1] They can also increase volatility under some conditions and even alter credit supply in markets not subject to any shocks.[2] While there is ample evidence that banks transmit financial shocks across markets, we know less about which types of markets are more likely to be impacted.[3]

This paper examines the role of borrower distance and the proximity of other lenders in the transmission of financial shocks. When multi-market banks adjust credit, are distant or closer firms more affected? Are shocks transmitted to firms far or close to competitors? Is the effect different for increases versus decreases? I attempt to answer these questions with a novel dataset of small business lending based on information from the Community Reinvestment Act (CRA) for 1999-2010. I focus on markets that were not directly impacted by, but were still exposed to credit supply shocks due to the physical presence of relatively smaller and funding constrained lenders in oil and residential booms. This helps compare the key factors in the allocation of positive and negative supply shocks – from oil and residential booms, respectively. In contrast to previous work, I measure lending at census tract groups *within* counties and rely on rich variation in the bank-borrower and borrower-competitor distance.

The existing evidence does not examine the effect of bank-borrower distance directly.[4] Instead, researchers define in-/out-market borrowers based on whether the lender has a physical office in the firm's local administrative area. Overall, the literature finds that positive supply shocks are allocated to in-markets, while negative ones primarily target out-markets, implying that the former are a source of rents due to lower cost of information production and monitoring. For example, oil booms increase mortgage supply to in-market

[1] For capital mobility e.g. Gilje et al. (2016), and Cortés and Strahan (2017). For resource allocation: Stiroh and Strahan (2003), Rice and Strahan (2010), Jayaratne and Strahan (1996).

[2] For volatility see Loutskina and Strahan (2015). For spillovers effects, see Morgan et al. (2004), Gilje et al. (2016), Imai and Takarabe (2011), and Berrospide et al. (2016). For substitution, see Loutskina and Strahan (2015) and Cortés and Strahan (2017).

[3] Credit crunch evidence from 2008-09 shows that relationship loans are less affected (Bolton et al., 2016).

[4] Only Sette and Gobbi (2015) uses bank-borrower distance in the context of negative supply shocks.

borrowers (Gilje et al., 2016). Exposure to high delinquencies reduces mortgage supply more for out-market borrowers (Berrospide et al., 2016). When lenders need liquidity after natural disasters, they reduce mortgage supply to out-markets (Cortés and Strahan, 2017).

This evidence has limited application for small business lending, about 90% of which goes to in-markets.[5] More importantly, the comparison of in-/out-markets highlights only competition between lenders with and without local presence. Since local lenders also compete for local borrowers, in-market competition can affect where they transmit financial shocks. The literature on local lending with asymmetric information provides testable implications. Agarwal and Hauswald (2010) show that firms closer to competitors are less likely to obtain credit and, if they do, it is at a lower price.[6] Therefore, markets away from competitors are more profitable and can attract most supply increases, while decreases in supply can target borrowers close to competitors. On the other hand, lenders can use their financial position opportunistically and grow or protect market share (Marquez, 2002; Bord et al., 2021).

My empirical results start with formalizing the mechanism behind the credit supply changes and confirming previous evidence.[7] I quantify the balance-sheet impact for banks using physical proximity to each boom and verify that above-average exposure to oil booms increases liquidity, while increased exposure to residential booms increases construction and development (C&D) lending, which can reduce the availability of funds for small businesses.[8]

Next, I test for credit supply shocks in indirectly-impacted markets with novel within-county business lending data. CRA lenders report originations by groups of census tracts with common income bracket designation. I focus on these areas, which include firms that borrow from the bank, and refer to the borrowers collectively as a census tract group.[9] I

[5] In-market lending is approximately 90% of total (Laderman et al., 2008; Anenberg et al., 2018). Adams et al. (2020) point that for individual lenders bank-borrower distance is stable.

[6] Degryse and Ongena (2005) provide similar distance-based results. Hauswald and Marquez (2006) and Marquez (2002) provide models of local lending with asymmetric information.

[7] Gilje (2017); Gilje et al. (2016); Plosser (2014) for oil and Chakraborty et al. (2018) for housing booms.

[8] Oil booms are based on the number of new oil wells, with bank exposure defined as above-average new wells in the proximity of branches. Residential booms are based on house price growth, with bank exposure defined as above-average growth in markets with bank presence.

[9] County, census tract, and income-bracket definitions are commonly defined for all banks, allowing me to track originations to the same group of census tracts within a county by different banks.

assume that the two closest branches – proportionately to their size – originate credit to each census tract group.[10] This helps generate a panel dataset of branch originations to different census tract groups, along with distance to the branch and to the competitors that also lend to the same area. To identify supply shocks, I compare originations in the same census tract group by branches of exposed relative to non-exposed banks. For each census tract group, I account for relationship-specific differences affecting the average lending of a branch and for demand shocks affecting annual total lending by all lenders. I find that higher liquidity from oil booms allows funding-constrained banks to originate more loans to borrowers far from these booms. I confirm that lenders with above-average exposure to residential booms reduce lending in census tract groups with more stable prices.

For my main results, I first examine how the bank-borrower distance impacts the estimated changes in credit, with a quasi diff-in-diff strategy based on continuous distance. The model compares whether the difference in originations between exposed and unexposed banks depends on the distance between the branch and the borrower. I find that originations by banks exposed to oil booms are higher for firms that are in the proximity. For credit reductions, I find no evidence that the affected lenders prioritize firms at a particular distance. It appears that positive shocks are allocated to firms about which the lender can easily acquire proprietary information – because they are close by, while negative shocks are allocated to borrowers for which proprietary information may not be relevant.[11]

For my most extensive results, I examine the effect of competitor proximity along with the bank's distance to the borrowers. I measure competitors' proximity with the fraction of other lenders which are closer than the lender's branch to the firm's census tract group.[12] This effect is identified within a quasi diff-in-diff setting which tests if the difference in originations

[10] This balances the likelihood that bigger and not closer branches originate credit (Presbitero et al., 2014).

[11] It should be noted that the oil boom is a positive deposit shock which can have a positive effect on all types of lending. In contrast, the residential boom leads to a re-allocation of lending from small business loans to real estate lending due to the increased profitability of such loans in a rising house price environment. This is relevant in the case of the role of distance because contracting lenders may reduce their small business loan portfolio more broadly regardless of the proximity to the borrower.

[12] Alternatively, I use an indicator of out-market borrowers.

between exposed and unexposed lenders is related to the fraction of other lenders that are closer to the bank's borrowers. I find that markets where the bank faces higher competition disproportionately benefit from the additional liquidity from oil booms. At the same time, these markets also face disproportionately higher decreases in supply when lenders attempt to free up liquidity in order to lend in residential booms. Together, the combined evidence suggests that building market share where the lender faces tougher competition is valuable but comes at a cost since the lender cannot discriminate between untested borrowers and those rejected by competitors. Additional liquidity helps support such costly market share expansion but lenders may not be able to justify the additional cost when they are in need of liquidity, and borrowers in such areas are likely to see lower supply of credit.

My key contributions are threefold. First, my study is the first to show that the previously documented credit supply effect of bank exposure to oil and residential booms also impacts small business credit.[13] This is an important extension as information frictions are pervasive in this segment. Second, I document that branch-borrower distance plays an important role – apart from competitor proximity – in the transmission of financial shocks and that the effect depends on the nature of the shock. Lenders supply more credit to closer firms but reduce loans for which distance is not a factor before reducing lending to more distant borrowers. Third, and most important, I show that proximity of other in-market lenders affects the transmission of financial shocks, independently from bank-borrower distance. Lending in markets where the bank faces higher competition is particularly sensitive to its financial state, both in the cases of increase and decrease in credit supply.[14] Decreases in supply have been documented to impact out-markets predominantly, as discussed above. I show that a similar dynamic occurs within in-markets: local lenders reduce supply in the proximity of competitors. Interestingly – and counter to previous evidence, I find that when lenders are

[13] Gilje et al. (2016) tested the effect of oil booms on mortgage originations, Chakraborty et al. (2018) focuses the effect of residential booms on bigger/more transparent firms, and Loutskina and Strahan (2015) examine how residential booms affect mortgage originations.

[14] With asymmetric information, higher share helps distinguish rejected from untested borrowers, creating an incentive to build and retain share. Therefore, markets where lenders expand during a positive shocks – close to other competitors – should be protected during negative shocks. My results provide mixed support.

in position to increase supply, they focus on the same markets close to competitors.

The results are relevant for the broad literature tracing intra-bank allocations of credit supply caused by proximity to an event affecting bank funding. Bustos et al. (2016) and Gilje et al. (2016) examine the effect of local liquidity shocks. Chakraborty et al. (2018) study the impact of exposure to residential booms, while Berrospide et al. (2016) focus on busts.[15] Neither of these studies examines how competition shapes the allocation of supply.

My evidence is also related to the literature on spatial lending competition and asymmetric information in local credit markets. The two papers closest to this study are Degryse and Ongena (2005) and Agarwal and Hauswald (2010) which examine the effects of bank-borrower and competitor-borrower distance. Gilje et al. (2016), Cortés and Strahan (2017), and Berrospide et al. (2016) also consider the importance of bank-borrower distance in limiting asymmetric information and generating rents but focus on in-/out-market borrowers.

My findings are related to the literature on financial deregulation and credit access. They suggest that the deregulation of cross-state banking in the US not only increases credit access with branches close to informationally opaque firms (Gilje et al., 2016) but also allows lenders to compete by originating close to other banks (Dell'Ariccia and Marquez, 2006). I show that these markets can be volatile and subject to the financial state of lenders.

Sections 2 describes the data sample. Section 3 formalizes the bank-level incentives for supply changes. Section 4 identifies the average supply shock in out-markets and 5 focuses on competition. Section 6 includes extensions, and 7 concludes.

2 Data, Sample Selection, and Definitions of Exposure

I start by detailing how I assemble the panel dataset of branch originations to different census tract groups, which is the main dataset used in the study. I discuss which banks are included in the sample and describe how the branches and borrowers of each bank are geo-located.

[15]Chakraborty et al. (2018) examine similar crowding out due to housing booms but mixes in- and out-markets and focuses on significantly bigger firms from DealScan. For additional examples of other local shocks see Cortés and Strahan (2017), Bord et al. (2021), Chavaz (2014), and Loutskina and Strahan (2015)

Finally, I outline how I establish a link between borrowers and lenders based on distance. After that, I describe how I define bank exposure to oil and real estate booms.

Banks: The sample includes independent commercial banks with \$250M+ in assets or \$1B+ bank-holding companies, which report small business lending in the Community Reinvestment Act (CRA) data for 1999-2010. Balance sheet and income statement variables are from the Call Reports. I exclude banks with below 50% loans- or deposits-to-assets, and 9% total risk-based capital ratios. The oil-boom sample covers 1999-2010 and the residential boom sample covers 1999-2006. Small banks have less than 40 branches or \$2B in assets. Since CRA increased the reporting cutoff to about \$1B in 2005, in the robustness section I also focus only on lenders above \$1B. I also examine the bigger community banks with assets between \$2B and \$10B in the robustness section.

Branches: I geocode branch locations of each bank using addresses from the FDIC's Summary of Deposits (SOD) data. This dataset also includes information on the total deposits held in each branch. I am able to locate 97.1% of all branches by relying on the Census geocoder.[16] Branches can move within a small area over the sample years, which prevents me from compiling a continuous time-series for each strictly based on addresses. Instead, I compare the geocoded locations in different years and assign the midpoint if the coordinates fall within 500 yards of each other. I use the precise coordinates of each branch to identify how many oil wells are created within a given distance.

Borrowers: I focus on small businesses and lending as defined by the CRA. These are businesses that receive commercial and industrial or other business loans below \$1M. I cannot locate individual businesses and their borrowing but, based on information from the CRA, can consistently identify the aggregated amount for well-defined areas within counties. The CRA data refers to standard census tracts and identifies five relative income brackets for the residents in each tract: Low, Moderate, Middle, Upper, and Not Known.[17] Each

[16] I also use the Open Street Map API for the addresses that cannot be located in the Census data. The Census and Open Street Map allow users to upload spreadsheets of addresses and return geo-coordinates. In the cases when both services fail, I used coordinates from another branch in the same city-zip code or city.

[17] For tract information see: https://www2.census.gov/geo/pdfs/education/CensusTracts.pdf. For relative

lender provides unique small business lending amounts for the group of census tracts with the same income bracket within each county. I use the group of census tracts with Low, Moderate, Middle, Upper or Not Known income in each county as the aggregated location of business borrowers, and I refer to these areas as a (firm/borrower) census tract group for short, with the understanding that these are groups of census tracts and not individual borrowers. County, census tract, and income-bracket definitions are commonly defined for all banks and do not change in my sample, allowing me to track the time series of originations to the same set of borrowers. Most importantly, I can compare how much two different banks are lending to the same census tract group within the county.

Matching Borrowers and Branches: To provide more detailed geographic information, I further break down the time series of a bank's lending to census tract groups within a county by identifying specific offices which provide the loans. I establish a relationship between borrowers and branches which is assumed to reflect which bank office was responsible for originating the loans to a given census tract group. I do this by allocating the amount of business lending in the tract group to the two closest branches. I use the amount of relative deposits across the two closest branches to split the lending amount to each branch. This allows me to measure how much a branch lends to different census tract groups, the distance to the borrowers in the tract group, and also the distance of branches of other banks to these borrowers. I compile the time series of lending by a branch to the same census tract group over time. By combining all branch originations to all census tract groups, I generate a panel of bank lending activity. This panel is the main dataset used in this study.

I link originations to the two closest branches rather than to the one closest branch, as is common in the literature on local lending, in order to make sure that bigger branches are always assumed to originate more credit. I aim to avoid associating new loans to a close but small branch when a bigger branch – including the bank headquarter – is slightly

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income brackets see: https://www.ffiec.gov/geocode/help3.aspx. The brackets are based on the tract Median Family Income (MFI) relative to the state or metro MFI. Low/Moderate/Middle/Upper brackets are <50%/>=50% and <80%/>=80% and <120%/>=120%. MFI is based on the 2000 Census.

farther away. This approach provides a balance between the literature on local lending, which focuses on the closest branches, and the transmission of financial shocks literature, e.g. Presbitero et al. (2014), which focuses on functional distance between borrowers and the headquarter. My approach also limits jumps in credit due to branch closures and openings.

I restrict the sample to markets within 375 miles of a branch, to limit highly transactional loans (Hannan, 2003; Adams et al., 2020), and highlight the sensitivity of my results to this assumption in the robustness section. The bottom panel of Table 1 provides some summary statistics that describe the loans to census tract groups. Originations grow by 1.25%, and much faster at small lenders, during the sample. Average count of loans decreases for all banks but increases for smaller lenders. The average branch-borrower distance is about 130 km (or about 80 miles).

Bank Competition: I define bank competitors as those lenders which originate loans to the same census tract group, i.e. lend to the same the group of county census tracts with the same income bracket. I calculate concentration with the HHI based on the share of lending originated by each active lender to the same census tract group. For my main results, I measure bank-specific competition by comparing the bank's distance relative to the rest of the lenders who lend to the same census tract group. I use the same approach to measure relative profitability and market share.

Fracking Wells, Bank Exposure to Oil Booms, and Sample: Co-ordinates and the dates of completion of oil wells during 1999-2010 come from the Homeland Infrastructure Foundation, which compiles surveys conducted by each state's department of natural resources.[18] The dataset includes close to 200k newly spudded wells, with about 15k new annual wells and a peak in 2006-2008 with 21k.[19] The map of new-wells data over time, in Figure 1, shows a clear expansion of drilling at both the intensive and extensive margins.

The existing fracking literature shows that drilling rights provides a significant payments for land owners of new wells (Plosser, 2014). I, therefore, focus on the number of new wells as

[18] https://hifld-geoplatform.opendata.arcgis.com/datasets/geoplatform::oil-and-natural-gas-wells/about

[19] There are a total of 72k wells in Texas, 12k in Louisiana, 17k in New Mexico, and 23k in Kansas.

a proxy for liquidity shocks.[20] I measure how many wells are formed within varying distance from each branch and summarize the overall exposure for each bank with the average wells per branch. The average branch has 1.6/7.2/16.7 wells within 15/30/45 miles, according to Table 1, and the average bank has 6.7 wells within 30 miles. Following evidence of how branch deposits respond to new wells at different distance I focus on wells within 30 miles and assume that banks with above-average number of wells within 30 miles are treated.

House Prices, Bank Exposure to Residential Booms, and Sample: Census tract and county house growth during 1999-2006 comes from FHFA's House Price Index (HPI), which follows newly-sold single-family prices changes, controlling for time-invariant unobservable effects. The housing boom sample covers 1999-2006. According to Figure 2, which maps annual census tracts appreciation, the run-up to the Great Recession had sustained growth with a strong regional component. Comparing 2000 to 2005, the year with the widespread growth, shows that coastal states experience the strongest appreciation. Outside of these growth is uneven, with a mix of high-growth and stable tracts. The second panel of Table 2 shows that the average HPI growth at borrower locations is 6.8%. The average HPI growth at branches is 6.7%.[21] Summarizing at the bank level, the average HPI growth across all borrower locations is 6.6%. I assume that lenders with above-average growth (6%) are exposed to real estate booms. This places 44% of banks in the high-growth category and only 36% up to 2003.

3 Drivers of Local Credit Supply Shocks

I briefly formalize the well-established mechanism behind the credit supply changes by estimating the balance sheet effect of geographic proximity to oil and residential booms, interpreting the evidence as clear incentives to adjust credit supply.[22]

[20]The well completion date is missing for Pennsylvania and North Dakota, which have a sizable wells.

[21]This is seen in the first panel. Branch HPI growth is based on the HPI in the county of the branch.

[22]Since balance sheet changes are more likely to impact credit supply at smaller lenders, owing to their limited ability to raise funds, I estimate the effect of exposure by bank size. I define small lenders as those

3.1 Oil Booms

Drilling using hydraulic fracturing accelerated during 2000-2010, increasing deposit growth for nearby banks as land-owners receive royalties (Gilje, 2017; Plosser, 2014). The increase in liquidity is evident in Table 1 for branches with above-average new wells in the proximity and for lenders with above-average wells per branch.[23] My branch-level tests are based on:

$$\begin{aligned}\ln \text{BranchDep}_{i,j,t} = {} & \alpha \ln \text{BranchDep}_{i,j,t-1} + \beta_s \text{NewWells}_{i,j,t-1} \times 1(\text{Small})_i \\ & + \beta_b \text{NewWells}_{i,j,t-1} \times 1(\text{Big})_i + \gamma X_{i,t-1} + \phi_{i,j} + \sigma_{j,t} + \epsilon_{i,j,t}\end{aligned} \tag{1}$$

where $\ln \text{BranchDep}_{i,j,t}$ is the log of deposits at branch j of bank i in year t. $\text{NewWells}_{i,j,t-1}$ is the number of new oil wells (scaled by 10) at a specific distance from j at $t-1$.[24][25] $X_{i,t-1}$ includes bank controls.[26] $1(\text{Small})_i/1(\text{Big})_i$ are indicators for small/big lenders. The branch panel data allows for fixed effects (FEs) for: i) branch ($\phi_{i,j}$) and year (σ_t), which compares if branches with more new wells see faster growth in the following year, relative to their own average, after controlling for annual growth differences; (ii) bank-year, which controls for annual bank-level growth differences, and compares branch performance within the bank by well proximity; (iii) metro-area-year, which controls for annual regional growth differences, and compares branches in the same area.

The bank test for liquidity shocks uses the following specification:

$$\begin{aligned}\ln \text{BankDep}_{i,t} = {} & \alpha \ln \text{BankDep}_{i,t-1} + \beta_s 1(\text{Fracking Boom})_{i,t-1} \times 1(\text{Small})_i \\ & + \beta_b 1(\text{Fracking Boom})_{i,t-1} \times 1(\text{Big})_i + \gamma X_{i,t-1} + \phi_i + \sigma_{st,t} + \epsilon_{i,t}\end{aligned} \tag{2}$$

with less than 40 branches or $2B in assets. In the robustness section I further examine the effect for banks with less than $10B in assets.

[23] Branch deposits grow 0.25% faster with above-average new wells. Lenders with above-average wells per branch have 9% deposit growth vs 8.7% for the rest, with non-transaction deposits growing 4.4% faster. The plot in Figure 3 further highlights the liquidity benefit from exposure.

[24] Wells are not likely to become operational right away so I focus on the the year after completion. In unreported specifications with both the current year and the lag, the latter dominates.

[25] Distance is based on the precise location of each branch and all oil wells.

[26] Control variables include the lags of Log of Assets, Deposits/Assets, C&I Loans/Assets, Mortgage Loans/Assets, Unused Loan Commitments / Assets, and the change in the number of branches.

where $\ln \text{BankDep}_{i,t}$ refers to the log of deposits at bank i during t. $1(\text{Fracking Boom})_{i,t-1}$ is an indicator for above-average new wells per branch for bank i at $t-1$. The number of new wells per branch for the bank is the sum of new wells within a given distance from each of its branches, divided by total branches. The liquidity effects, β_s/β_b, are estimated within a single-difference specification, comparing deposits at lenders with above-average wells per branch to the rest, after controlling for the bank (ϕ_i) and yearly differences (σ_t).[27]

Table 3 reports branch deposit estimates. Columns (1)-(3) feature varying levels of proximity to new wells and suggest that liquidity is higher at shorter distances – particularly for smaller bank branches. Since focusing on wells within 15 miles substantially limits the number of exposed banks, I measure the liquidity shock with new wells within 30 miles. Column (1) suggests that at this distance, 10 additional wells increase small-bank deposits by 0.2% in the following year. The effect is similar in column (4), where identification is based on within-bank variation, and in column (5), based on annual within-state variation.[28]

The bottom panel of Table 3 quantifies the composite liquidity effect of branch proximity to wells on bank deposits and interest expense.[29] Column (1) suggests that small lenders with above-average exposure to wells within 30 miles see 1.75% faster deposit growth. Allowing for regional differences lowers the impact to 1.5% but estimates are still statistically significant.[30] The estimate is similar to the 2.5% growth in Gilje et al. (2016) with somewhat different exposure definition and HMDA lenders. The results for non-transaction deposits are consistent with the overall deposits and are pronounced in the case of core deposits, which increase by 2.2%. Columns (7)-(8) provide mixed evidence on interest expense, but rule out the case that banks incurred additional costs during the higher-liquidity periods.

[27] I also add bank-HQ x Year FE, accounting for annual growth at other lenders in the same HQ state.
[28] This is also the case after controlling for annual state-bank and metropolitan area differences.
[29] I estimate models with bank FE and year FE or headquarter-state-year FE. The second model controls for regional shocks that deliver additional deposit growth even for lenders that are not close to oil booms.
[30] Liquidity effects for big lenders are positive but not statistically significant.

3.2 Residential Booms

The existing literature suggests that residential appreciation improves collateral values, which reduces credit risk, and allows lenders to expand real estate lending in booming areas. The summary statistics in Table 2 are consistent with this hypothesis – lenders with above-average appreciation have 0.5%/1.7%/4.1% faster growth of total/RE/C&D lending.[31] This re-allocation can reduce the availability of funds for small businesses – particularly in non-booming areas.[32] I test for differences in total real-estate and C&D loans at banks with above-average house price growth with the following specification:

$$\begin{aligned} \ln \text{BankLoans}_{i,t} = \alpha \ln \text{BankLoans}_{i,t-1} + \beta_s 1(\text{RE Boom})_{i,t} \times 1(\text{Small})_i \\ + \beta_b 1(\text{RE Boom})_{i,t} \times 1(\text{Big})_i + \eta X_{i,t-1} + \phi_i + \sigma_{st,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $\ln \text{BankLoans}_{i,t}$ refers to the log of total, real estate, or C&D loans for bank i in year t. $1(\text{RE Boom})_{i,t}$ is an indicator for lenders with above-average house-price appreciation. I measure appreciation based on: the county of each bank branch or the census tract group of its borrowers. The empirical model is identified in a first-difference setting which compares credit differences at lenders whose branch network exposes them to above-average residential appreciation to the rest. The relative difference, reflected by β_s/β_b, accounts for invariant bank-specific factors, ϕ_i, and for annual differences in loan growth common to all lenders, σ_t, or across all lenders within the same headquarter state, $\sigma_{st,t}$.

The estimates in Table 4 are in line with the descriptive differences: banks with higher exposure lend between 1% to 5% more, particularly C&D loans. Columns (1)-(3), pooling all bank sizes and including year FE, imply that total loans are 1.04% higher, real estate loans are 1.25% higher, and C&D loans are 6.16% higher. The latter is 5.3% higher after

[31] Figure 4 highlights the relationship between exposure to higher housing appreciation and loan growth, by focusing on smaller lenders. It shows that the proportion of lenders with loan growth over 12% is significantly higher for those with above-average appreciation.

[32] Chakraborty et al. (2018) argues that the booming housing market creates highly profitable lending opportunities which are pursued by cutting lending in other sectors, such as commercial loans. According to Loutskina and Strahan (2015), they also increase collateral values, which reduces credit risk in the bank's portfolio, and further encourages lenders to focus on booming markets.

accounting for regional trends (with a headquarter-state-year FE). Breaking down the effect by bank size and controlling for bank state, in column (5), shows that proximity to booms is similarly associated with higher lending at big and small lenders. Columns (6)-(8) use different exposure proxies and arrive at similar estimates. 1% increase in average borrower census tract group HPI is associated with 1.35% higher C&D lending. Similar increase in average HPI at branch counties raises loans by 1.16%.

4 Credit Supply Shocks

Bank presence – through local branches – in markets with many new oil wells or appreciating house prices is associated with balance sheet changes which can affect credit supply at lenders with funding constraints. Banks which cannot easily raise new capital or securitize loans can transmit these changes to other markets across their branch network. I quantify the impact in these outlying – with respect to the source of the shock – markets, while in the next section I examine the role of borrower distance and competition. I focus on small lenders, where adjustments in credit supply are expected from theoretical and empirical perspective.[33]

4.1 Empirical Methodology

Higher liquidity from oil booms allows for additional lending due to the increase in deposits, while residential booms and increased C&D lending can reduce the availability of funds for other forms of lending due to the reallocation of funding from non-booming to booming markets. The geographical source of treatment implies that there are markets outside the direct impact, affected indirectly through the internal allocation of credit supply. In such markets the presence of oil-boom treated banks can be associated with positive credit supply

[33]For a discussion of capital or borrowing constraints at lenders see Kashyap and Stein (1995); Stein (1998); Thakor (1996). Smaller banks depend less on brokered deposits or interbank loans due their informationally intensive and/or geographically concentrated portfolio (Berger et al., 2001, 2005).

shocks, while residential-boom treated banks can cause credit supply reductions.[34] Despite the distinct context of each boom, the consistent definition of lending, local markets, and competition helps identify the key strategic incentives in the allocation of credit supply.

I identify credit supply shocks with the following specification:

$$\begin{aligned} \ln \mathrm{SBL}_{i,j,m,t} = \alpha \ln \mathrm{SBL}_{i,j,m,t-1} + \beta_s 1(\mathrm{Boom})_{i,t} \times 1(\mathrm{Small})_i \\ + \beta_b 1(\mathrm{Boom})_{i,t} \times 1(\mathrm{Big})_i + \zeta X_{i,t-1} + \phi_{i,j,m} + \eta_{m,t} + \epsilon_{i,j,m,t} \end{aligned} \tag{4}$$

where $\ln \mathrm{SBL}_{i,j,m,t}$ is the log of small business originations by branch j of bank i to firms in census tract group m in year t.[35] In other words, this is the amount of lending originated by bank i to the set of firms located in the group of census tracts m through one of its two nearest branches j. $1(\mathrm{Boom})_{i,t}$ is an indicator for whether bank i is exposed to either of the booms.[36] $X_{i,t-1}$ include bank-level controls defined above.

My empirical strategy focuses on firms not directly impacted by the event which affects the bank's financial position. This limits the demand effects stemming directly from each of the booms.[37] I use geographical distance between firms and new wells and focus on firms which are at least 60 miles away from new wells in the previous, current, and following year.[38] I assume that at this distance it is unlikely that borrowers will directly benefit from oil booms. Similarly, to identify firms which are not likely to directly benefit form real estate booms, I focus on areas with below-average HPI in the past, current, and following year.

The panel dataset of branch originations to different census tract groups provides several dimensions of variation which allow for rich definition of FE, including: (i) branch by census

[34] Note that these are different types of shocks. The oil boom increases credit supply to all types of lending, while the residential boom decreases commercial and industrial lending because of the profitability of real estate lending.

[35] Note that m represents borrowers located in a group of census tracts within a county which have one of the five different income brackets.

[36] For oil booms: indicator for above-average new wells per branch for bank i during the preceding year. For residential booms: indicator for above-average house-price growth during the current year.

[37] Gilje (2017) argues that liquidity from oil discoveries boosts local lending and economic growth in the immediate proximity. This can also potentially lead to endogenous residential appreciation. Both of these place a hurdle on the propagation of liquidity shocks in outlying markets.

[38] The firms location is based on the centroid of the census tract group.

tract group FE, $\phi_{i,j,m}$, controls for the average originations by the branch to borrowers in census tract group m; (ii) census tract group by year FE, which controls for the originations by all lenders to the census tract group m during year t.[39]

The identification of supply shocks, captured by β_s/β_b, is done within a first-difference setting. I compare originations by branches of exposed bank i to firms in census tract group m to originations by branches of non-exposed banks to the same census tract group m, after controlling for the average lending that each branch does to m and for the annual overall lending to census tract group m. I report the impact for small banks whose originations can be constrained by deposits.

I will not identify supply shocks if demand shocks vary by bank exposure or if non-exposed banks are also impacted. Demand shocks can vary by the treatment status if lenders serve a subset of the local market that is distinct from other lenders. Here, the underlying population of borrowers is uniform since the relative income level is the same, which assures that treated banks lend to the same borrowers as the untreated banks. To make sure that non-exposed banks are not also impacted, I rely on the results from the previous section which highlighted key differences in balance sheet variables related to my definitions of treatment. I further limit the sample of borrowers in order to reduce the set of untreated banks and make sure that they are far from either of the booms.

4.2 Estimation Results

Oil Booms: Results from exposure to oil booms are listed in Table 5. Column (1), with a branch FE, finds that treated small banks have 22% higher originations relative to all other untreated lenders, or about 20% of standard deviation of origination growth. The estimate increases to 24% in column (2), after controlling for time-invariant census tract group differences in total lending. In column (3), I allow total lending to a census tract group to vary annually, achieving identification by comparing current branch lending by

[39]More broadly, this FE accounts for demand-driven or otherwise common shocks to lending, including trends.

exposed bank to branch lending by non-exposed banks within the same census tract group. The estimated effect increases to 27%. Finally, in column (4) I allow for branch by census tract group FE and census tract group by year FE which extends the identification in column (3) by further controlling for the average lending by a branch to a census tract group. The specification allows for the possibility that all lenders increase lending in any given year, implying that, in this case, treated banks do so at a faster pace, in line with having more liquidity. The estimated effect in this case is the highest: 29%, or 25% of standard deviation of lending growth. Column (5) focuses on the count of loans and finds a 18% increase. The effect for big banks is either small in magnitude or not statistically significant.

Exposure to oil booms is associated with higher supply of small business lending by small lenders in markets that are not subject to such booms.[40] Originations outpace other lenders far from the source of increased liquidity, suggesting that the affected banks transmit liquidity shocks through their network of branches, generating supply shocks for borrowers in the out-markets. This supports the hypothesis that increased liquidity, stemming from wells proximity, allows funding-constrained banks to originate more loans.

Since 60 miles may not be far enough from oil booms, I examine census tract groups 90, 120, and 150 miles away, in (6)-(8). Originations are 31% and 24% higher in the first two cases, suggesting that treated banks transmit additional liquidity at a significant distance. The set of treated banks declines as I further restrict the sample to markets farther away: in column (8) the sample is almost half of the baseline and the estimated effect approaches zero as the number of markets with small treated banks also goes to zero.

Housing Booms: Table 6 provides estimates of credit supply shock in markets with stable prices. I start with examining the baseline effect and change the definition of markets not subject to residential booms. With a branch FE, in (1), treated banks have 6.6% lower originations relative to those without exposure to highly-appreciating markets. Accounting for time-invariant differences across borrowers, in (2), further increases the impact to 9.1%.

[40] The results are consistent with Gilje et al. (2016), who find that oil booms increases lending by 20% of standard deviation of mortgage growth.

The highest decrease (10.4%) for banks exposed to housing booms is estimated in column (3), which allows for time-varying shocks across borrower areas. In (4) and (5), treated banks underperform other lenders by 9.5% in loan volume and by 6.3% in loan count. The volume difference represents about 8% of a standard deviation for loan growth. The estimated effect for big banks in my preferred specification, in column (4), is not statistically significant.

Residential appreciation is associated with reductions in the supply of small business lending by smaller lenders in markets with more stable house prices.[41] The estimates account for common changes in demand for loans by borrowers with similar income level and imply that exposed banks reduce supply relative to other lenders. The results are not driven by differences in market growth since this is reflected in the census-tract-group by year FE. The fact that originations at treated banks are lower in markets that are not the source of treatment suggests that proximity to residential booms and the associated expansion in C&D loans generates a supply shock for markets not subject to shocks.

Distinguishing between markets subject to residential booms is critical for the identification strategy. Markets with below-average appreciation can be an important growth source for untreated banks which lack access to markets with higher growth. In this case the main effect is overestimated since the market-level shock includes higher supply by untreated banks. If this type of allocation within markets without residential booms by untreated banks is at play, locations with even lower growth should have smaller *relative* difference for treated banks. I find no evidence for such reallocation by untreated banks in columns (6) and (7), which show that treated banks reduce even more in markets with lower growth.

5 The Effect of Distance and Competition

There is substantial evidence that the proximity between the bank and the borrower impacts the cost of information acquisition (Berger et al., 2005) and monitoring (Coval and

[41] My results are close to Chakraborty et al. (2018) who find a 13.4% decrease in lending for one standard deviation increase in house-price exposure. Their credit segment and identification strategy differ but highlights the same crowding-out mechanism.

Moskowitz, 2001), and reflects the level of information frictions, which are endemic in the context of small business lending. As a result, in equilibrium banks lend less to borrowers away from their branches due to the lower precision of credit screens (Agarwal and Hauswald, 2010). Even after liquidity shocks, they tend to focus primarily in the proximity of branches where lenders can generate accurate information (Gilje et al., 2016). In the case of re-allocation of lending across markets, Cortés and Strahan (2017) provide evidence that lenders limit originations first in distant markets, where they lack informational advantage.

Following this literature, I examine the importance of borrower-lender distance for the propagation of supply shocks. I expect that additional liquidity from oil booms should generate disproportionate increases for borrowers that are closer. Conversely, when lenders re-allocate funding towards real estate lending in booming markets, they will disproportionately reduce originations for borrowers farther away. In other words, lenders expand where they have an information advantage and lending is more profitable, and contract where they lack this advantage and do not generate rents.

Local competition can also influence the allocation of credit supply. There are several theoretical studies which emphasize the importance of strategic factors in the small business credit segment, independently from the role of distance, e.g. Broecker (1990); Von Thadden (2004). Increasing market share provides additional value in models by Dell'Ariccia (2001) and Marquez (2002) because it allows lenders to discriminate between untested and borrowers rejected by competitors. Consequently, higher share softens competition for those with prior relationship and generates rents (Agarwal and Hauswald, 2010). This incentive to build and retain share is behind the opportunistic behavior highlighted by Bord et al. (2021). Since the lender is likely to have lower market share where other lenders are closer, due to their higher informational advantage (Hauswald and Marquez, 2006; Agarwal and Hauswald, 2010), markets where other lenders are in the proximity can become an attractive target for credit expansion by banks exposed to oil booms. Conversely, retaining market share close to other lenders can be important and can limit the reduction in originations by lenders looking to free up liquidity in order to lend more in residential booms.[42]

So far, I have discussed the implications of exposure to oil and residential booms as mirror images of each other – the former increases credit supply to small businesses, while the latter decreases it. However, there are important distinctions when it comes to the role of distance and competition in how each of the two shocks are propagated. First, the oil boom is a positive deposit shock which can have a positive effect on all types of lending. In contrast, the residential boom leads to a re-allocation of lending from small business loans (or commercial and industrial loans) to real estate lending due to the increased profitability of real estate loans in a rising house price environment. This is relevant in the case of the role of distance because contracting lenders may reduce their small business loan portfolio more broadly regardless of the proximity to the borrower. Second, because of asymmetric information, higher market share allows lenders to discriminate between rejected and untested borrowers, creating an incentive to both build and retain market share. This means that the markets where lenders expand during a positive shocks – close to other competitors – are not likely to be the markets where lenders contract during negative shocks.

5.1 Empirical Methodology

The role of bank-borrower distance is examined with the following specification:

$$\begin{aligned}\ln \mathrm{SBL}_{i,j,m,t} = {} & \beta_s 1(\mathrm{Boom})_{i,t} \times 1(\mathrm{Small})_i + \sigma_s 1(\mathrm{Boom})_{i,t} \times 1(\mathrm{Small})_i \times \mathrm{Distance}_{i,j,m,t} \\ & \beta_b 1(\mathrm{Boom})_{i,t} \times 1(\mathrm{Big})_i + \sigma_b 1(\mathrm{Boom})_{i,t} \times 1(\mathrm{Big})_i \times \mathrm{Distance}_{i,j,m,t} \\ & + \zeta X_{i,t-1} + \phi_{i,j,m} + \eta_{m,t} + \epsilon_{i,j,m,t}\end{aligned} \tag{5}$$

[42]Some markets may also have more profitable borrowers regardless of the proximity of other lenders. Lenders with higher liquidity can target such markets, assuming that capacity constraints prevent lenders from arbitraging all borrowers (Paravisini, 2008). I measure relative profit generated by other lenders to proxy for the relative profitability from lending in a given market.

Notation follows equation 4 except for the interaction with $\text{Distance}_{i,j,m,t}$, which refers to the distance between the originating branch j of bank i and the census tract group m.[43] For ease of interpretation, I center this measure at the sample mean. The key coefficient of interest is σ_s and it reflects the variation in the credit supply shock, identified by β_s, as a function of distance to the borrower. It is identified within a quasi difference-in-difference setting since distance is a continuous variable and not an indicator. The model compares whether the origination difference between exposed and unexposed banks depends on the distance between the branch and the borrower.

Higher borrower-lender distance increases the transportation or information costs, making lending more transactional and less profitable. Following this, a negative estimate of σ_s in the case of exposure to oil booms suggests that positive credit supply is allocated relatively more to borrowers that are closer. Such an estimate in the case of exposure to residential booms will imply that when reducing lending to free liquidity for booming areas, affected banks limit originations more strongly for distant borrowers.

I examine the importance of competition by further extending the empirical model and adding interactions with competitor distance:

$$\begin{aligned}
\ln \text{SBL}_{i,j,m,t} = {} & \beta_s 1(\text{Boom})_{i,t} \times 1(\text{Small})_i + \sigma_s 1(\text{Boom})_{i,t} \times 1(\text{Small})_i \times \text{Distance}_{i,j,m,t} \\
& + \gamma_s 1(\text{Boom})_{i,t} \times 1(\text{Small})_i \times \text{CompetitorDistance}_{i,j,m} \\
& + \beta_b 1(\text{Boom})_{i,t} \times 1(\text{Big})_i + \sigma_b 1(\text{Boom})_{i,t} \times 1(\text{Big})_i \times \text{Distance}_{i,j,m,t} \qquad (6) \\
& + \gamma_b 1(\text{Boom})_{i,t} \times 1(\text{Big})_i \times \text{CompetitorDistance}_{i,j,m} \\
& + \zeta X_{i,t-1} + \phi_{i,j,m} + \eta_{m,t} + \epsilon_{i,j,m,t}
\end{aligned}$$

$\text{CompetitorDistance}_{i,j,m}$ reflects the proximity of other lenders to the bank's borrowers in census tract group m. First, I measure this with an indicator for whether the census tract group m is in a county where bank i has no branches. This measure is used by Gilje et al.

[43] Since distance to the borrower may be endogenous with respect to each shock, I also estimate the model using distance measured at the beginning of the sample. Results are reported in the robustness section.

(2016), without controlling for the distance between the branch j and the borrowers in m, to capture the composite effect of being relatively farther from the borrowers compared to other lenders. Here, I follow Agarwal and Hauswald (2010) who decompose the effect of proximity into lender distance to borrowers and the proximity of other competitors to the borrowers. $1(\text{Boom})_{i,t} \times \text{Distance}_{i,j,m,t}$ controls for the first effect, while $1(\text{Boom})_{i,t} \times \text{CompetitorDistance}_{i,j,m}$ uses variation in the proximity of competitors to borrowers at the same distance to identify the second effect. When I use the no-branch county indicator, the effect is identified in a diff-in-diff setting which compares if the difference between originations of exposed banks relative to unexposed depends on the branch presence in a county, holding distance to the borrowers constant.

For my key results, I measure the proximity of competitors with the fraction of other lenders which are closer than branch j to census tract group m.[44] Having all competitors be closer puts the lender at a relative disadvantage because other banks are closer to its borrowers in m and can poach them. I use the fraction of closer lenders as opposed to the 25th percentile of distance of competitors, as in Agarwal and Hauswald (2010), in order to focus on relative advantage, not its intensity. This effect is identified within a quasi diff-in-diff setting which compares if the difference in originations of exposed lenders relative to unexposed is related to the fraction of other lenders that are closer to the bank's borrowers.

A positive γ_s in the case of exposure to oil booms suggests that additional liquidity is prioritized to borrowers that are closer to other lenders, regardless of the distance between the branch j and borrowers in m. This is suggestive of an incentive to expand the loan share to reduce asymmetric information. Consistent with this, in the case of exposure to residential booms, a positive γ_s implies that banks which free up additional liquidity by reducing originations away from booms maintain lending in markets close to competitors.

Finally, I examine whether credit supply is allocated to more profitable markets. I mea-

[44] I use the median of the fraction of lenders that are closer to the borrower to fully incorporate lenders that may not originate loan during every year but are still in the proximity. Since this measure can be endogenous with respect to the shocks, I also estimate the model with the measure at the beginning of the sample. Results are reported in the robustness seciton.

sure relative profitability similarly to relative distance of competitors – with the fraction of other lenders who also lend to borrowers in m with higher return on assets. Markets where all other lenders are more profitable are likely to be desirable for banks with additional liquidity from oil booms exposure. Such markets are likely to be shielded from negative supply shocks by banks with exposure to residential booms. Both suggest a positive estimate for γ_s.

It is important to acknowledge that while the bank-level shock may be plausibly exogenous to the amount of small business lending, the distance between the borrower and the closest branch is not. For example, it can be the case that banks open new branches as part of a competitive re-allocation as in Bord et al. (2021). This is especially true during the real estate booms as banks can open new branches in areas where they were doing a lot of real estate lending. If these are areas where the bank was also doing small business lending, such practice can impact my estimates of the importance of distance and competition. In order to minimize concerns related to such endogeneity, I continue to restrict the sample of firms (i.e. census tract groups) – as was the case in the previous section, to those outside of oil/residential booms occurring in the preceding, current, and next year. This limits the possibility that lending in my samples is directly related to current or expected booms, since it requires that lenders can predict where such booms will occur at least two years in advance. Furthermore, I have followed the approach used by Gilje et al. (2016) to deal with the possible endogeneity by including the change in bank branches as a bank-level control in all of my regressions. Finally, in the robustness section I provide results based on distance and competition measures as of the start of the sample, which are consistent with a limited role for endogeneity.

5.2 Estimation Results

Positive Credit Supply Shocks: The estimation results are listed in Table 7. Column (1) estimates the model only with branch-borrower distance and finds that positive supply shocks are relatively higher for borrowers that are in close proximity to the lender. At mean distance, exposed banks originate 30% more credit relative to other lenders who also lend to the same census tract group. For census tract groups located one standard deviation farther from the closest branch, this difference falls down to 16%. Absent other controls for competition, the decline reflects a combination of less accurate information and stronger competition.

In column (2), I add an indicator for borrowers in counties where the bank has no branches, in addition to the branch-borrowers distance, to examine the allocation to areas where the exposed bank is at a disadvantage. I find that the difference in originations between exposed and non-exposed lenders is 40% for borrowers in no-branch counties compared to 16% in counties where the exposed bank has branches. I introduce a more precise measure of competitor proximity in column (3), which includes the fraction of lenders that are closer to the bank's borrowers. The estimates suggest that exposed banks allocate 70% more credit to markets with one standard deviation higher fraction of closer competitors, compared to 38% more at the mean of this fraction.[45] The results from the two different measures of competitor – distance-based – advantage suggest that lenders with additional liquidity prioritized markets where they are at a disadvantage due to the proximity of other lenders. Such markets are likely more costly to get into because the lender is unable to discriminate between untested and borrowers rejected by competitors. Additional liquidity may allow exposed lenders to overcome this by building up valuable market share.[46]

In column (4), I test if positive supply shocks are allocated to markets that are relatively more profitable for the affected lender. I find limited evidence for this with a positive but not statistically significant estimate.

I examine whether the allocation of supply shocks varies with the underlying market structure, using the HHI based on loan shares at the same area of borrowers.[47] In columns

[45] One standard deviation is 18%.

[46] This strategic incentive is highlighted in Dell'Ariccia (2001); Marquez (2002) where expanding market share provides a key informational advantage.

[47] I divide markets into three categories with HHI cutoffs at roughly 1000 and 1700, which correspond to

(5)-(10), I report estimates for markets with medium concentration. The estimate of branch-borrower distance in column (5) is negative but not statistically significant. The remaining evidence suggests that this is due to competing negative effect of branch-borrower distance and positive effect of borrower-competitor proximity.

Column (6) adds the no-branch county indicator. The estimate is positive, while the effect of branch-borrower distance is negative and marginally significant. This suggests that banks with additional liquidity are more likely to go beyond the counties where they have branches and expand lending in markets where other lenders have physical presence. In column (7), the effect of treatment is about double in medium-concentrated markets where the fraction of closer-located lenders is one standard deviation above the sample average. The fact that supply shocks continue to prioritize markets where exposed banks are disadvantaged even when these markets have higher concentration – and as a result information frictions are likely higher – suggests that affected banks focus on areas where higher market share can be particularly valuable.

In column (8), I find evidence that treated banks also expand in markets that are relatively more profitable. The estimates in column (9) and (10), further supports this by showing that both higher value of market share and higher profitability guide the allocation of supply.

Negative Credit Supply Shocks: Table 8 lists results for the allocation of negative credit supply shocks. Column (1) includes only the branch-borrower distance and does not show evidence that the affected lenders prioritize borrowers at a particular distance. They are equally likely to reduce originations for borrowers at any distance. This is consistent with the notion that exposure to residential booms makes C&I loans less attractive compared to RE loans, leading to a broad reduction in small business lending regardless of the bank-borrower distance. In other words, the exposed lender frees up liquidity by focusing on the

limited, moderate, and high concentration, following the Department of Justice Merger Guidelines (Pilloff, 2005). I divide the sample into three equally-size categories. In the oil sample the cutoffs are 1000 and 1700; in the residential booms sample they are 1300 and 1900.

overall business segment or industry rather than targeting borrowers at a particular distance.

In column (2), I include the indicator for borrowers in no-branch counties, in addition to branch-borrower distance. I find that exposed banks reduce originations more strongly in markets where they lack physical presence compared to where they do. In markets where they are not facing such competition and where they have branches, borrowers are not subject to negative credit supply shocks. In column (3), I replace the indicator with the measure of proximity of competitors to the borrower and find a negative but not statistically significant estimate. The combined evidence from column (2) and (3) suggests that affected lenders reduce originations disproportionately more in areas where they do not have branches but the specific relative distance of competitors does not matter. Finally, I do not find evidence in column (4) that relative profitability is an important factor behind the credit allocation.

Columns (5)-(10) focus on the sample of markets with medium/high concentration of lenders.[48] Column (5) only features branch-borrower distance and, as in the full sample, find no evidence that the bank distance to the borrower determines where credit supply is reduced. Including the indicator for borrowers in no-branch counties, in column (6), suggests that physical presence of the affected bank does not impact the allocation of credit. In contrast, the evidence from column (7), which includes the relative proximity of competitors, implies that exposed banks are likely to disproportionately reduce originations to borrowers that are closer to competitors. There is a stronger credit reduction in concentrated markets where competitors are in the proximity: one standard deviation higher fraction of closer-lenders (18%) is associated with double the decrease compared to that at the average, or 53% reduction versus 27%. Together, the evidence from columns (6)-(7) points to a similar conclusion as in the full sample, from columns (2)-(3). Lenders looking to free up liquidity in order to expand real estate lending in areas with residential booms are more likely to reduce credit in markets where they are at a disadvantage relative to the competition. Conversely, they protect borrowers in markets where the competition is lower by not systematically

[48] I include markets with medium and high concentration since the sample with just medium is very small. I divide the sample into three equally-size categories using 1300 and 1900 as cutoffs.

reducing lending. Finally, I do not find evidence that relative profitability matters for the allocation of credit supply in markets with higher concentration.

5.3 Summary and Discussion

The evidence of how branch-borrower distance affects the allocation of credit supply shocks suggests that distance to the borrower matters for expansions in credit but not necessarily for contractions. It appears that when allocating additional liquidity, lenders focus on borrowers in the proximity, where contracting frictions are lower. When reducing credit, affected lenders appear to focus on borrowers at different distances. It is possible that such borrowers rely on transactions loans with lower information frictions or that affected banks reduce small business lending across the board. From this perspective, we can summarize the effect of borrower distance – and the information frictions it embodies – on the allocation of credit supply as follows. Positive shocks are allocated to borrowers about which the lender can easily acquire proprietary information – because they are close by, while negative shocks are allocated to borrowers for which proprietary information may not be relevant or borrowers who, as a whole, are less profitable. The latter is a possible result of the fact that the negative shock results from bank exposure to more profitable types of lending, which can lead to a broad reduction in lending to small businesses regardless of the bank-borrower distance. This can explain why reductions do not depend on distance.

The evidence of how the proximity of other lenders affects the allocation of credit supply shocks suggests that originations in markets where the bank faces higher competition are sensitive to the liquidity state of the affected bank. These markets disproportionately benefit from the additional liquidity from exposure to oil booms and see much higher increase in credit supply. At the same time, these markets also face disproportionately higher decreases in credit supply when lenders attempt to free up liquidity in order to lend in residential booms. Together, the combined evidence suggests that building market share where the lender faces tougher competition is valuable but comes at a cost since the lender cannot discriminate between untested borrowers and those rejected by competitors. Additional liquidity helps support such costly market share expansion but lenders may not be able to justify the additional cost when they are in need of liquidity, and borrowers in such areas are likely to see lower supply of credit.

6 Robustness and Extensions

In this section, I provide evidence of the sensitivity of the main results with respect to several assumptions in generating the sample data and limitations of the CRA data. I also provide some extensions of the main results.

Change in CRA Reporting Criteria: The CRA reporting requirement changed in 2005 when the cutoff for minimum bank assets was increased from $250M to about $1B. Given my definition of small banks as those with less than $2B in assets or fewer than 40 branches, this introduces changes in the sample starting in 2006 with fewer smaller banks reporting. This can be a particular problem for the real estate boom period since the sample changes in 2006, just as the boom ends. To examine whether this change affects the main results, I first introduce Small x Year FE to account for differences in the sample average for small banks over time, and, second, drop from the sample banks larger than $1B. The estimation results are provided in Table 9. The liquidity impact of fracking is reduced slightly, while the re-allocation impact of residential booms is strengthened by this change. The results imply that the change in the CRA reporting criteria does not affect the main results.

Including More Distant Loans in the Sample: The main results focus on loans within 375 miles of the branch. Table A1 explores the sensitivity of these with respect to this constraint by including loans within approximately 600 miles and by including all loans. The table indicates that the main coefficients remain consistent.

Definition of Small Banks: The main results assume that small banks are those with less than \$2B in assets or less than 40 branches. According to FDIC (2012) there is some consensus regarding how to define community banks with most studies focusing on lenders with less than \$1B in assets, while for supervision purposes this cutoff being set at \$10B. Table A2 reports results for bigger community banks with less than \$10B in assets. The estimates suggest that such lenders do not propagate credit supply shocks in accordance with smaller lenders. This supports the interpretation in the main section that only smaller lenders with limited ability to raise additional funding consistently respond to liquidity shocks or are forced to reduce lending when re-allocating resources to more profitable areas.

Alternative Specification of Distance and Competition Measures: I re-estimate the main results related to distance and competition using measures as of the beginning of each sample. This should alleviate concerns that the results are driven by opportunistic behavior by lenders who respond to each shock by changing their network. The estimates are provided in Table 10 and 11. The changes in coefficient estimates are minimal suggesting that such endogeneity concerns are accounted for by my empirical design.

Are Branches More Important in Propagating Shocks to Lower-Income Areas?: In Table 12, I utilize the reported income level of the census tract groups in order to examine whether the propagation of shocks by branches depends on the local income. In particular, branches may be more important in propagating shocks to lower-income areas, where soft information may play a more prominent role. The results from the liquidity shock are consistent with this interpretation. The coefficient estimate for low-income census tract groups is close to three times bigger compared to the moderate-middle income areas. However, this effect is not as sensitive to distance from the lending branch, which is the case with moderate-middle income areas. The results from the reallocation due to residential booms suggest that the majority of the reduction is comes from higher income areas. This is consistent with the interpretation that exposed lenders are likely to focus on loans where they do not have a comparative advantage.

Are Lenders Competing for Firms with Lower Information Frictions?: One of the key main results is that lenders take advantage of additional liquidity by increasing small business lending supply in the proximity of other competitors. This prediction features in Marquez (2002) who states that a lender with larger capacity should compete for a larger fraction of the free market, since higher market share increases the informational advantage over other banks. However, expanding close to competitors is less profitable because they are likely to include unsuccessful borrowers rejected by the nearby competitors (Hauswald and Marquez, 2006). In order to understand how oil-boom-exposed lenders pursue market share in high-risk markets, I break down originations by loan size. Berger and Black (2011) argue that banks, who can take advantage of hard information lending, have a comparative advantage in lending to small and large firms. I examine whether small lenders expand market share by hardening soft information, which allows them to increase supply of relatively small and big firms.

I test this by reproducing the key main results focusing only on these loan sizes in Table 13. The left panel shows that in the case of fracking the majority of additional credit is concentrated in the very small or larger loan segment. Smaller loans is where the use of credit scoring is predominant. The majority of large loans are underwritten with hard information pertaining to established firms substantial financial information. The estimates are consistent with the interpretation that banks with additional liquidity target markets where share is valuable by focusing on the segments where screening by closer lenders is less effective at softening competition.

The right panel of Table 13 sheds light on the segments that see biggest reduction by banks that reallocate supply towards housing booms and away from out-markets. Column (2) shows that the majority of the decline is in large loans, consistent with the interpretation that lenders protect valuable market share. Loans to bigger firms are underwritten with quantifiable information that might be easier to find, which reduces the competitive value of screening and allows lenders to more easily compete at distance.

Are Lenders Competing for Higher-quality Firms?: The literature on local lending under asymmetric information documents that higher quality firms, i.e. with higher credit score, are more likely to switch lenders if they are closer to competing lenders (Agarwal and Hauswald, 2010). This suggests that lenders with higher liquidity due to oil booms may focus on expanding supply first to higher quality firms that are located close to competitors. Conversely, they may disproportionately reduce supply to firms of lower quality when reducing close to competitors. While I cannot directly observe firm quality, I can examine whether the allocation of shocks differs by the income bracket of each census tract group. For example, I can test if firms in higher income census tract groups are more likely to experience higher increases in credit, when they are closer to competitors. I can also examine if middle-income census tract groups see higher reductions in supply, closer to competitors, by banks exposed to residential booms.

Table 14 reports estimates of the main results from model 6 for the sub-samples of moderate-middle and upper income census tract groups.[49] The results for oil booms suggest that the expansion in supply closer to competitors documented in the main results focuses on higher-income census tract groups. This is consistent with the view that competition is tougher for higher-quality firms. The results for residential booms suggest that the reduction in supply closer to competitors is concentrated in middle-income census tract groups. If these locations are more likely to include lower-quality firms, the evidence supports the interpretation that competing in markets with higher-risk firms is more costly when the lender is at a disadvantage.

7 Conclusion

This paper provides new evidence about the transmission of financial shocks across the branch network of smaller, funding constrained lenders. I focus on two geographically delineated events – new oil wells and appreciation of house prices – which have been previously

[49]Moderate-middle income census tract groups have median family income (MFI) 50% to 120% of the state MFI. Upper income tracts have MFI over 120%.

documented to generate supply effects in markets far from where they occur. With novel data of *within* county lending, this paper is the first to confirm that exposure to oil and residential booms impacts supply of credit to small businesses in other markets. I go beyond identifying the average change in credit and examine how it differs across markets with varying levels of information frictions and competition.

I measure information frictions with branch-borrower distance and document that it plays an important role in the transmission of financial shocks. I find that the effect depends on the nature of the shock. Lenders supply more credit to closer borrowers but reduce loans for which distance is not a factor before reducing lending to more distant borrowers. I measure local competition with the proximity of other in-market lenders to the bank's borrowers. I document that proximity of competitors affects the transmission of financial shocks, independently from bank-borrower distance. Lending in markets where the bank faces higher competition is particularly sensitive to its financial state, both in the cases of increase and decrease in credit supply. I show that supply falls more in the proximity of competitors. In contrast to previous evidence, I find that when lenders are in position to increase supply, they focus on the same markets close to competitors.

My results suggest that branches do not simply integrate local markets with limited arm's length financing because their specialized information acquisition limits contracting frictions. They also play an important role in competition. Given additional liquidity, lenders contest the informational advantage of competitors and increase lending where they are not as good at acquiring specialized information.

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Tables and Figures

Table 1: Summary Statistics: Sample of Exposure to Oil Booms

The panel provide summary statistics for the sample of branches for banks reporting loan originations in the CRA data during 1999-2010. Wells within X miles reports the number of newly spudded wells within X distance of the branch. Is Small? is an indicator for branches part of an institutions with less than 40 branches or $2B in assets. Deposit growth refers to the branch.

Branch-level variables	All Branches		Wells in 30miles≥1		Wells in 30miles>6	
	Mean	SD	Mean	SD	Mean	SD
Wells within 15 miles	1.6132	(11.3451)	9.4169	(26.0357)	14.5563	(31.5593)
Wells within 30 miles	7.2425	(38.9822)	42.1185	(85.8394)	64.6973	(101.112)
Wells within 45 miles	16.7071	(74.0065)	93.4061	(155.7057)	135.1574	(180.3765)
Is Small?	25.9515	(43.8369)	27.7138	(44.7588)	27.5423	(44.6731)
Deposit Growth	9.0257	(39.8018)	8.9759	(39.1576)	9.1415	(39.8012)
Deposit Growth x Small	12.1771	(40.9698)	11.3814	(41.1766)	11.7958	(40.6971)
N	564329	NA	85654	NA	54320	NA

The panel reports bank-level statistics for banks in the fracking sample. Wells within 30 miles lists the average wells per branch within 30 miles i.e. it averages at the banks level the number of newly spudded wells across all bank branches. Deposit growth refers to the bank total.

Bank-level variables	All Banks		Mean Wells in 30miles>0		Mean Wells in 30miles >6	
	Mean	SD	Mean	SD	Mean	SD
Wells within 30 miles	6.7556	(30.073)	24.923	(53.7036)	45.946	(67.803)
Is Over 7 Wells within 30 miles	14.1517	(34.8564)	52.2088	(49.9561)	100	(0)
Is Over 7 Wells within 30 miles x Small	10.9651	(31.2463)	40.4613	(49.0865)	77.4991	(41.7667)
Deposit Growth	9.8907	(18.4272)	8.6649	(16.5024)	8.9952	(16.5932)
Deposit Growth x Small	9.8102	(17.1425)	8.6275	(15.6435)	9.063	(15.8674)
Core Deposit Growth	10.1454	(21.9525)	9.4177	(18.1644)	9.6075	(18.35)
Non-transaction Deposit Growth	11.1259	(20.2815)	9.7764	(18.9586)	10.196	(18.9018)
Branch Growth	6.0485	(19.8598)	5.5279	(20.1256)	6.019	(17.6266)
Log Assets	13.3172	(1.2124)	13.7566	(1.5202)	13.617	(1.4371)
Deposits to Assets	79.1156	(8.621)	78.7018	(9.1412)	79.5485	(8.9091)
Loans to Assets	70.1799	(9.8971)	69.0654	(9.7918)	68.2054	(9.7969)
ROE	11.1733	(10.1861)	11.6633	(9.8611)	12.072	(8.7126)
Total Risk-Based Capital Ratio	13.6995	(4.5512)	13.2897	(3.7633)	13.5208	(4.0539)
Net Charge-offs to Loans	0.3658	(0.9075)	0.4072	(0.6617)	0.3826	(0.5927)
Log Unused Commitments	11.2652	(1.5827)	11.6376	(1.9977)	11.4703	(1.9022)
N	18894	NA	5116	NA	2671	NA

The table lists statistics from the panel dataset of census-tract group loans originated by each bank branch. Columns under All Banks refer to the summary statistics of census tract lending by all lenders in the oil boom sample. Columns under Treated Banks focus on the census tract lending by banks considered to be exposed to oil booms. Finally, the last two columns focus on the census tract group lending originated by treated banks in census tract groups at least 60 miles away from oil wells. Business Loans Growth refers the change in the bank's originations. HHI is calculated using market shares of all lenders in the same census tract. X > % Others in Firm Census Tract refers to the faction of other lenders for which the bank has higher X.

Census Tract Group Variables:	All Banks		Treated Banks		Treated Banks (Tracts > 60miles from wells)	
	Mean	SD	Mean	SD	Mean	SD
Is Small?	32.111	(46.6903)	16.7718	(37.3617)	3.6037	(18.6384)
Over 7 Wells within 30 miles x Small	4.6306	(21.0147)	16.7718	(37.3617)	3.6037	(18.6384)
Wells within 60 miles of Firm Census Tract	44.6288	(150.2806)	118.5253	(238.5248)	0	(0)
Business Loans Growth	1.2514	(121.4973)	-2.2692	(120.7558)	-2.3631	(114.1458)
Business Loans Growth x Small	4.5831	(126.2207)	-0.1684	(126.968)	0.7028	(117.2116)
Business Loan Count Growth	-1.0352	(74.8641)	-1.8385	(71.0318)	-0.1993	(70.1982)
Business Loan Count x Small	0.5578	(74.9566)	-2.645	(74.7348)	-1.3506	(70.4317)
HHI	17.6116	(11.7175)	19.3068	(12.5505)	18.1294	(11.2998)
HHI x Small	17.2824	(12.0486)	19.4117	(13.4117)	16.4555	(11.1745)
Branch-Firm Census Tract Distance	130.4172	(154.1893)	176.015	(168.4871)	233.517	(179.1224)
ROA > % Others in Firm Census Tract	38.1032	(22.9724)	38.185	(22.4781)	39.924	(21.2505)
ROA > % Others in Firm Census Tract x Small	37.9782	(23.4567)	38.8911	(23.3048)	45.9483	(21.9894)
ROE > % Others in Firm Census Tract	44.5572	(25.5086)	48.5119	(25.929)	52.0284	(24.7696)
ROE > % Others in Firm Census Tract x Small	44.0068	(25.7758)	46.9185	(26.7915)	56.8106	(24.1683)
Int Expense < % Others in Firm Census Tract	57.9722	(24.6539)	61.2161	(22.9888)	64.5238	(22.3354)
Int Expense < % Others in Firm Census Tract x Small	52.7115	(25.5041)	53.157	(24.6678)	55.2627	(21.8925)
Lending Dist < % Others in Firm Census Tract	76.822	(17.6766)	74.8023	(17.3831)	69.5568	(17.0934)
Lending Dist < % Others in Firm Census Tract x Small	86.5443	(13.4672)	87.0107	(12.5524)	82.0734	(14.7219)
Loan Share > % Others in Firm Census Tract	64.6708	(29.0283)	66.1744	(29.428)	69.0824	(27.909)
Loan Share > % Others in Firm Census Tract	62.4592	(28.975)	64.9495	(29.1044)	61.7113	(28.1461)
N	863018	NA	238257	NA	41874	NA

Table 2: Summary Statistics: Sample of Exposure to Residential Booms

The panel reports bank-level summary statistics for the sample of banks that report CRA originations during 1999-2006. Is Average HPI > 6? is an indicator for banks with average HPI across all lending areas of over 6%. Average HPI refers to HPI at the lending locations, while HPI at Branch County measure county HPI for counties where the bank has branches. Loan growth refers to the bank total.

Bank-level variables	All Banks		Average HPI>0		Average HPI >6	
	Mean	SD	Mean	SD	Mean	SD
Is Average HPI > 6?	43.5942	(49.5903)	43.985	(49.6393)	100	(0)
Average HPI	6.5964	(4.631)	6.6651	(4.5933)	10.4983	(4.3945)
Average HPI at Branch County	6.6689	(4.9847)	6.5674	(4.7569)	10.1251	(4.7313)
Is Small?	87.6802	(32.8675)	82.755	(37.779)	79.7063	(40.223)
Loan Growth	11.9425	(20.6198)	10.4911	(18.5399)	12.4314	(20.8413)
Loan Growth x Small	11.9226	(19.6828)	10.2652	(16.8658)	12.424	(18.984)
RE Loan Growth	13.8156	(26.2501)	12.1604	(22.321)	13.8276	(25.1521)
Const and Dev Loan Growth	24.7668	(58.2596)	22.772	(55.0739)	26.866	(61.4318)
Branch Growth	6.9884	(21.0184)	5.9812	(19.7696)	6.2095	(21.9998)
Log Assets	13.1047	(1.2148)	13.4008	(1.2543)	13.5917	(1.336)
Deposits to Assets	79.9085	(8.7637)	79.0083	(8.9756)	78.5722	(9.3439)
Loans to Assets	69.0486	(9.8206)	68.7029	(9.5847)	68.6814	(9.7554)
ROE	13.0472	(7.9429)	13.5637	(7.4179)	13.537	(7.7253)
Total Risk-Based Capital Ratio	13.8159	(4.5821)	13.5115	(4.1806)	13.5393	(4.3597)
Net Charge-offs to Loans	0.2716	(0.772)	0.2777	(0.7648)	0.2206	(0.6427)
Log Unused Commitments	11.0207	(1.5923)	11.3679	(1.6204)	11.6436	(1.6951)
N	15260	NA	10374	NA	4563	NA

The table lists statistics from the panel dataset of census-tract group loans originated by each bank branch. Columns under All Banks refer to the summary statistics of census tract lending by all lenders in the residential boom sample. Columns under Treated Banks focus on the census tract lending by banks considered to be exposed to residential booms. Finally, the last two columns focus on the census tract lending originated by treated banks in census tract groups considered as not exposed to residential booms (with HPI below 6%). For additional information about variable definitions refer to Table 1.

Census Tract Group variables:	All Banks		Treated Banks		Treated Banks (Tracts with HPI<6)	
	Mean	SD	Mean	SD	Mean	SD
Is Small?	36.2446	(48.0707)	28.9155	(45.3371)	9.7378	(29.6477)
Is Average HPI>6? x Small	14.9882	(35.6956)	28.9155	(45.3371)	9.7378	(29.6477)
Average HPI	6.8446	(5.8835)	9.5887	(6.4613)	3.3091	(1.777)
Business Loans Growth	7.9431	(119.0526)	9.2037	(115.2784)	12.1121	(110.7683)
Business Loans Growth x Small	9.0068	(125.4051)	9.4062	(123.5431)	9.1275	(125.3449)
Business Loan Count Growth	4.1785	(74.3327)	6.6846	(73.1908)	12.6691	(71.6739)
Business Loan Count Growth x Small	3.4845	(75.8066)	4.1794	(75.2798)	7.9986	(73.2887)
HHI	17.1477	(11.0871)	15.2205	(10.1798)	17.5885	(9.9547)
HHI x Small	16.8352	(11.4268)	13.6347	(9.7546)	17.2552	(10.8399)
Branch-Firm Census Tract Distance	123.3557	(151.2731)	143.4044	(165.426)	210.4389	(174.7199)
ROA > % Others in Firm Census Tract	37.7383	(21.9516)	38.7303	(22.3964)	38.2161	(20.3209)
ROA > % Others in Firm Census Tract x Small	37.3169	(23.2547)	39.2517	(24.3294)	41.1294	(24.8716)
ROE > % Others in Firm Census Tract	44.3771	(24.3484)	45.112	(24.5976)	45.3281	(21.7344)
ROE > % Others in Firm Census Tract x Small	42.4903	(25.1223)	45.2631	(25.6607)	48.281	(23.5164)
Int Expense < % Others in Firm Census Tract	57.6756	(25.1814)	60.443	(25.1883)	59.3953	(24.9222)
Int Expense < % Others in Firm Census Tract x Small	53.9175	(26.11)	57.9031	(25.7531)	57.7976	(25.1259)
Lending Dist < % Others in Firm Census Tract	75.4194	(18.2183)	72.9316	(18.3503)	67.193	(16.7614)
Lending Dist < % Others in Firm Census Tract x Small	85.6874	(13.9371)	84.6839	(14.3573)	83.2665	(16.1146)
Loan Share > % Others in Firm Census Tract	65.8109	(28.863)	64.5264	(28.8067)	66.4249	(29.0106)
Loan Share > % Others in Firm Census Tract	63.6377	(28.7573)	61.3601	(28.1071)	63.4136	(27.9511)
N	554141	NA	83056	NA	2551	NA

Table 3: Effect of Oil Boom Proximity on Branch and Bank Deposits

The panel lists estimates from the branch-level model 1. Deposits refers to the log of deposits at a branch j of bank i in year t. Wells within x miles refers to the number of new oil wells at a specific distance from branch, during year $t-1$. I scale this number in tens of wells to help with legibility. Additional unreported controls includes the lags of Log of Assets, Deposits/Assets, C&I Loans/Assets, Mortgage Loans/Assets, Unused Loan Commitments / Assets, and the change in the number of branches, whose estimates are suppressed. The lag of deposits is also suppressed. Small refers to lenders with less than 40 branches or $2B in assets. The sample include annual branch observations during 2000 to 2010. Residuals are clustered at the branch level. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Deposits	(2) Deposits	(3) Deposits	(4) Deposits	(5) Deposits	(6) Deposits	(7) Deposits
Wells within 30miles$^{Small}_{t-1}$	0.00191***			0.00171**	0.00160***	0.00160**	0.00156**
	(0.000448)			(0.000666)	(0.000462)	(0.000665)	(0.000689)
Wells within 30miles$^{Big}_{t-1}$	-0.000139			0.000708*	0.000281	0.000674	0.000516
	(0.000391)			(0.000402)	(0.000405)	(0.000418)	(0.000522)
Wells within 15miles$^{Small}_{t-1}$		0.00431***					
		(0.00126)					
Wells within 15miles$^{Big}_{t-1}$		-0.00183					
		(0.00119)					
Wells within 45miles$^{Small}_{t-1}$			0.000976***				
			(0.000272)				
Wells within 45miles$^{Big}_{t-1}$			4.54e-05				
			(0.000206)				
Observations	481,515	481,515	481,515	480,523	481,509	480,521	480,497
R-squared	0.957	0.957	0.957	0.961	0.958	0.961	0.962
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes				
Year x Bank FE				Yes			Yes
Year x State FE					Yes		
Year x Bank x State FE						Yes	
Year x Metro FE							Yes

The panel lists estimates from the bank-level model 2. Deposits refers to the log of deposits at bank i at year t. NonTrDep, CoreDep, IntExp refer to non-transaction deposits, core deposits, and interest expense. $1(\text{Fracking})_{i,t-1}$ is an indicator for above-average new wells per branch for bank i during the preceding year, $t-1$. Additional unreported controls are the same controls as in the branch-level model. Columns (3)-(4), deposit growth with the log of non-transaction deposits with a specification including the lag, which is also suppressed. Columns (5)-(6) similarly examine the log of core deposits, while (7)-(8) look at interest expense. The sample include annual bank observations during 2000 to 2010. Residuals are clustered at the bank. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Deposits	(2) Deposits	(3) NonTrDep	(4) NonTrDep	(5) CoreDep	(6) CoreDep	(7) IntExp	(8) IntExp
Fracking$^{Small}_{t-1}$	0.0177***	0.0151**	0.0188**	0.0162*	0.0215**	0.0219**	-0.00422	0.00486
	(0.00654)	(0.00674)	(0.00820)	(0.00834)	(0.00971)	(0.00990)	(0.0160)	(0.0169)
Fracking$^{Big}_{t-1}$	0.0214*	0.0195	0.0115	0.00856	0.0256*	0.0219	-0.0339	0.0158
	(0.0125)	(0.0123)	(0.0150)	(0.0154)	(0.0140)	(0.0136)	(0.0235)	(0.0242)
Observations	18,636	18,611	17,536	17,511	18,634	18,609	18,636	18,611
R-squared	0.992	0.992	0.989	0.990	0.986	0.988	0.934	0.940
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes		Yes		Yes		Yes	
Year x HQ State FE		Yes		Yes		Yes		Yes

Table 4: Effect of Residential Boom Proximity on Bank Lending

The table lists estimates from model 3. Loans is the log of total loans, RE Loans is the log of real estate loans, ConstrDev is the log of construction and development loans for bank i in year t. $1(\text{RE Boom})_{i,t}$ is an indicator for above-average exposure to housing appreciation. Loan Area HPI is the continuous measure of bank-average HPI. Loan area refers to the set of borrowers within a county with common relative income bracket. Branch HPI over 6% refers to the indicator of bank average appreciation over 6% using branch-county HPI. Branch HPI is the continuous measure of bank-average HPI at branch counties. $X_{i,t-1}$ includes the same controls as in Table 3. HQ State refers to the state in which the bank is headquartered. The sample include annual bank observations for 2000 to 2006. Residuals are clustered at the bank. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Loans	(2) RE Loans	(3) ConstrDev	(4) ConstrDev	(5) ConstrDev	(6) ConstrDev	(7) ConstrDev	(8) ConstrDev
RE Boom_t	0.0104**	0.0125**	0.0616***	0.0529***				
	(0.00409)	(0.00499)	(0.0145)	(0.0189)				
RE $\text{Boom}_t^{\text{Small}}$					0.0527***			
					(0.0200)			
RE $\text{Boom}_t^{\text{Big}}$					0.0543**			
					(0.0262)			
Loan Area HPI_t						0.0135***		
						(0.00375)		
Branch HPI over 6_t							0.0523***	
							(0.0179)	
Branch HPI_t								0.0116***
								(0.00305)
Observations	9,979	9,971	9,777	9,772	9,772	9,772	12,583	12,583
R-squared	0.993	0.989	0.950	0.952	0.952	0.953	0.930	0.930
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes					
Year x HQ State FE				Yes	Yes	Yes	Yes	Yes

Table 5: Oil Booms Exposure and Local Loan Originations

The table lists estimates from model 4. SBL is the log of small business originations by branch j of bank i to census tract m in year t. Census tract m refers to the group of census tract within a county with the same relative income bracket. Fracking_{t-1} is an indicator for whether bank i is exposed to an oil boom – above-average number of new oil wells (within 30 miles) per branch. Small refers to the coefficient estimate for banks with less than 40 branches of $2B in assets. The specifications include but suppress coefficients for additional controls listed in the notes in Table 3 and the lag of SBL. Columns vary by the FE specifications included as well as the census tract groups that are excluded from the sample. Columns (1)-(5) exclude census tract groups with any new wells in the previous, current, and next year within 60 miles. Columns (6)-(8) progressively exclude tracts within 90, 120, and 150 miles from new wells. Residuals are clustered at the census tract. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) SBL	(2) SBL	(3) SBL	(4) SBL	(5) Count	(6) SBL	(7) SBL	(8) SBL
$\text{Fracking}_{t-1}^{\text{Small}}$	0.224***	0.242***	0.270***	0.286***	0.178***	0.309***	0.236**	-0.0336
	(0.0787)	(0.0763)	(0.0807)	(0.0699)	(0.0463)	(0.0758)	(0.118)	(0.134)
$\text{Fracking}_{t-1}^{\text{Big}}$	-0.0652***	-0.0621***	-0.0381**	-0.0137	-0.0115	-0.00901	-0.0192	-0.00811
	(0.0148)	(0.0147)	(0.0163)	(0.0160)	(0.0113)	(0.0184)	(0.0212)	(0.0244)
Observations	149,238	149,238	149,238	150,547	150,547	129,382	108,107	80,858
R-squared	0.722	0.748	0.811	0.906	0.942	0.905	0.904	0.910
Branch FE	Yes	Yes	Yes					
Census Tract Group FE		Yes						
Census Tract Group x Year FE			Yes	Yes	Yes	Yes	Yes	Yes
Branch x Loan Area FE				Yes	Yes	Yes	Yes	Yes
Distance from Fracking Over	60 miles	60 miles	60 miles	60 miles	60 miles	90 miles	120 miles	150 miles

Table 6: Residential Booms Exposure and Local Loan Originations

The table lists estimates from model 4. SBL is the log of small business originations by branch j of bank i to census tract m in year t. Census tract m refers to the group of census tract within a county with the same relative income bracket. RE Boom_t represents an indicator for lenders with above-average residential appreciation. Small refers to the coefficient estimate for banks with less than 40 branches of $2B in assets. The specifications include but suppress coefficients for additional controls listed in the notes in Table 3 and the lag of SBL. Columns vary by the FE specifications included as well as the lending locations that are excluded from the sample (as defined by the Firm Census Tract Groups w HPI below). Columns (1)-(5) exclude census tract groups with less than 6% HPI during the previous, current, and next year. Columns (6)-(7) progressively exclude census tract groups with less than 5% and 4$ appreciation. Residuals are clustered at the census tract. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) SBL	(2) SBL	(3) SBL	(4) SBL	(5) Count	(6) SBL	(7) SBL
RE $\text{Boom}_{t-1}^{\text{Small}}$	-0.0660*	-0.0910**	-0.104**	-0.0961**	-0.0644**	-0.152**	-0.0908
	(0.0392)	(0.0377)	(0.0458)	(0.0385)	(0.0254)	(0.0674)	(0.0961)
RE $\text{Boom}_{t-1}^{\text{Big}}$	0.0492***	0.0363**	0.0585***	0.00559	0.0185*	0.00843	0.0885***
	(0.0157)	(0.0153)	(0.0191)	(0.0161)	(0.0109)	(0.0204)	(0.0306)
Observations	69,570	69,570	69,570	70,320	70,320	43,490	19,134
R-squared	0.755	0.785	0.840	0.934	0.956	0.940	0.949
Branch FE	Yes	Yes	Yes				
Census Tract Group FE		Yes					
Census Tract Group x Year FE			Yes	Yes	Yes	Yes	Yes
Branch x Census Tract Group FE				Yes	Yes	Yes	Yes
Census Tract Groups w HPI below	6pct	6pct	6pct	6pct	6pct	5pct	4pct

Table 7: Positive Supply Shocks: Role of Branch-Borrower Distance and Competition

The table lists estimates from models 5 and 6. Fracking_{t-1} represents an indicator for above-average number of new oil wells (within 30 miles) per branch. $\text{Distance}_{i,j,m,t}$ refers to the (de-meaned) distance between the originating branch j of bank i and the firm census tract m. $\text{CompetitorDistance}_{i,j,m}$ reflects the proximity of other lenders to the bank's borrowers in census tract m. This is measured with two different variable below: No-Branch Cnty – an indicator for census tract in a county without local branch, and Fr Closer Banks – the fraction of other lenders which are closer than the originating branch to the borrower's census tract. Fr More Profit Banks is a continuous variable capturing the proportion of lenders in the census tract with higher ROA than the originating bank. Fr Bigger Share Banks is similarly defined but captures the fraction of banks with bigger share in the census tract. Coefficient estimates for big banks are included in the specification but not reported in the table. Also suppressed are additional controls listed in the notes in Table 3 and the lag of SBL. Columns (1)-(4) include the entire sample, (5)-(10) include a subset with HHI between 1000 and 1700. Residuals are clustered by the census tract. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) SBL	(2) SBL	(3) SBL	(4) SBL	(5) SBL	(6) SBL	(7) SBL	(8) SBL	(9) SBL	(10) SBL
$\text{Fracking}_{t-1}^{\text{Small}}$	0.298***	0.164*	0.384***	0.304***	0.354**	-0.0266	1.006***	0.926***	1.255***	0.999***
	(0.0725)	(0.0991)	(0.0789)	(0.0795)	(0.179)	(0.217)	(0.267)	(0.233)	(0.258)	(0.226)
$\text{Fracking}_{t-1}^{\text{Small}}$ x Distance	-0.000967**	-0.00143***	-0.00209***	-0.000942**	-0.00120	-0.00231*	-0.00695***	-0.00120*	-0.00539***	-0.00183**
	(0.000406)	(0.000490)	(0.000641)	(0.000388)	(0.000843)	(0.00135)	(0.00200)	(0.000706)	(0.00167)	(0.000759)
$\text{Fracking}_{t-1}^{\text{Small}}$ x No-Branch Cnty		0.235*				0.549**				
		(0.134)				(0.267)				
$\text{Fracking}_{t-1}^{\text{Small}}$ x Fr Closer Banks			1.479**				6.436***		4.733***	
			(0.660)				(1.667)		(1.492)	
$\text{Fracking}_{t-1}^{\text{Small}}$ x Fr More Profit Banks				0.163				4.779***	3.610***	5.655***
				(0.406)				(1.267)	(1.206)	(1.279)
$\text{Fracking}_{t-1}^{\text{Small}}$ x Fr Bigger Share Banks										1.138*
										(0.653)
Distance	-0.0283***	-0.0283***	-0.0283***	-0.0283***	-0.0304***	-0.0304***	-0.0303***	-0.0304***	-0.0304***	-0.0302***
	(0.000932)	(0.000932)	(0.000933)	(0.000932)	(0.00172)	(0.00172)	(0.00172)	(0.00172)	(0.00172)	(0.00172)
No-Branch Cnty		-0.157				0.690*				
		(0.240)				(0.412)				
Observations	150,547	150,547	150,547	150,547	49,721	49,721	49,721	49,721	49,721	49,721
R-squared	0.906	0.906	0.906	0.906	0.900	0.900	0.900	0.900	0.900	0.900
Branch x Loan Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Area x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Concentration Level	All	All	All	All	Med	Med	Med	Med	Med	Med

Table 8: Negative Supply Shocks: Role of Branch-Borrower Distance and Competition

The table lists estimates from models 5 and 6. RE Boom$_t$ and represents an indicator for lenders with above-average residential appreciation. Distance$_{i,j,m,t}$ refers to the (de-meaned) distance between the originating branch j of bank i and the firm census tract m. CompetitorDistance$_{i,j,m}$ reflects the proximity of other lenders to the bank's borrowers in census tract m. This is measured with two different variable below: No-Branch Cnty – an indicator for census tract in a county without local branch, and Fr Closer Banks – the fraction of other lenders which are closer than the originating branch to the borrower's census tract. Fr More Profit Banks is a continuous variable capturing the proportion of lenders in the census tract with higher ROA than the originating bank. Fr Bigger Share Banks is similarly defined but captures the fraction of banks with bigger share in the census tract. Coefficient estimates for big banks are included in the specification but not reported in the table. Also suppressed are additional controls listed in the notes in Table 3 and the lag of SBL. Columns (1)-(4) include the entire sample, (5)-(10) include a subset with HHI over 1000. Residuals are clustered by the census tract. Notation: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	SBL	SBL	SBL	SBL	SBL	SBL	SBL	SBL	SBL	SBL
RE Boom$^{\text{Small}}_{t-1}$	-0.0976**	0.0477	-0.145**	-0.0971**	-0.106**	-0.0189	-0.267***	-0.106**	-0.271***	-0.0984**
	(0.0387)	(0.0586)	(0.0564)	(0.0388)	(0.0481)	(0.0732)	(0.0904)	(0.0479)	(0.0918)	(0.0470)
RE Boom$^{\text{Small}}_{t-1}$ x Distance	0.000218	0.000752*	0.000928	0.000212	-0.000473	-7.98e-05	0.00137	-0.000475	0.00141	-0.000199
	(0.000440)	(0.000457)	(0.000614)	(0.000435)	(0.000612)	(0.000663)	(0.000945)	(0.000611)	(0.000960)	(0.000707)
RE Boom$^{\text{Small}}_{t-1}$ x No-Branch Cnty		-0.202***				-0.120				
		(0.0722)				(0.0919)				
RE Boom$^{\text{Small}}_{t-1}$ x Fr Closer Banks			-0.579				-1.482**		-1.519**	
			(0.431)				(0.660)		(0.672)	
RE Boom$^{\text{Small}}_{t-1}$ x Fr More Profit Banks				-0.0255				-0.0409	-0.106	-0.0580
				(0.207)				(0.255)	(0.258)	(0.255)
RE Boom$^{\text{Small}}_{t-1}$ x Fr Bigger Share Banks										-0.191
										(0.245)
Distance	-0.0290***	-0.0290***	-0.0290***	-0.0290***	-0.0254***	-0.0254***	-0.0255***	-0.0254***	-0.0255***	-0.0254***
	(0.00129)	(0.00129)	(0.00129)	(0.00129)	(0.00160)	(0.00160)	(0.00160)	(0.00160)	(0.00160)	(0.00160)
Observations	70,320	70,320	70,320	70,320	47,005	47,005	47,005	47,005	47,005	47,005
R-squared	0.934	0.934	0.934	0.934	0.939	0.939	0.939	0.939	0.939	0.939
Branch x Loan Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Area x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Concentration Level	All	All	All	All	Med/Low	Med/Low	Med/Low	Med/Low	Med/Low	Med/Low

Table 9: Robustness: CRA Reporting Criteria Change

The table lists estimates from model 4. The table replicates the results from Tables 5 and 6 by adding a $1(\text{Small})_i xYear$ FE and further restricting the sample of banks to those with assets over \$ 1B. For additional details about notation, please consult Table 5. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) SBL	(2) SBL
$\text{Fracking}^{\text{Small}}_{t-1}$	0.238***	0.263***
	(0.0707)	(0.0860)
$\text{Fracking}^{\text{Big}}_{t-1}$	-0.00186	0.00184
	(0.0162)	(0.0169)
Observations	150,547	115,919
R-squared	0.906	0.914
Branch x Census Tract Group FE	Yes	Yes
Census Tract Group x Year FE	Yes	Yes
Small x Year FE	Yes	Yes
Distance from Fracking Over	60 miles	60 miles
Sample	All	Assets > 1B

VARIABLES	(1) SBL	(2) SBL
$\text{RE Boom}^{\text{Small}}_{t-1}$	-0.127***	-0.209***
	(0.0393)	(0.0705)
$\text{RE Boom}^{\text{Big}}_{t-1}$	0.0366**	0.0242
	(0.0169)	(0.0179)
Observations	70,320	50,159
R-squared	0.934	0.944
Branch x Census Tract Group	Yes	Yes
Census Tract Group x Year FE	Yes	Yes
Small x Year FE	Yes	Yes
Census Tract Group w HPI below	6pct	6pct
Sample	All	Assets > 1B

Table 10: Robustness of Positive Supply Shocks: Alternative Specification of Branch-Borrower Distance and Competition

The table lists estimates from models 5 and 6. Fracking_{t-1} and represents an indicator for above-average number of new oil wells (within 30 miles) per branch. The table replicates Table 7 measuring Distance, Fraction of Closer Banks, and Fraction of More Profitable Banks as of the start of the sample – indicated as $t = 0$. For additional definitions, please consult Table 7. Notation: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	SBL	SBL	SBL	SBL	SBL	SBL
$\text{Fracking}_{t-1}^{\text{Small}}$	0.300***	0.380***	0.304***	0.360**	0.796***	0.432*
	(0.0727)	(0.0751)	(0.0736)	(0.181)	(0.251)	(0.231)
$\text{Fracking}_{t-1}^{\text{Small}}$ x Distance (t=0)	-0.000920**	-0.00191***	-0.000873**	-0.00122	-0.00426***	-0.00125
	(0.000399)	(0.000546)	(0.000387)	(0.000825)	(0.00152)	(0.000812)
$\text{Fracking}_{t-1}^{\text{Small}}$ x Fr Closer Banks (t=0)		1.390***			4.276***	
		(0.539)			(1.408)	
$\text{Fracking}_{t-1}^{\text{Small}}$ x Fr More Profit Banks (t=0)			0.181			0.602
			(0.280)			(0.848)
Observations	150,547	150,547	150,547	49,721	49,721	49,721
R-squared	0.906	0.906	0.906	0.900	0.900	0.900
Branch x Loan Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Area x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Market Concentration Level	All	All	All	Med	Med	Med

Table 11: Robustness of Negative Supply Shocks: Alternative Specification of Branch-Borrower Distance, and Competition

The table lists estimates from models 5 and 6. RE Boom$_t$ and represents an indicator for lenders with above-average residential appreciation. The table replicates Table 7 measuring Distance, Fraction of Closer Banks, and Fraction of More Profitable Banks as of the start of the sample – indicated as $t = 0$. For additional definitions, please consult Table 8. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) SBL	(2) SBL	(3) SBL	(4) SBL	(5) SBL	(6) SBL
RE Boom$^{\text{Small}}_{t-1}$	-0.0983**	-0.114***	-0.0997***	-0.109**	-0.169***	-0.109**
	(0.0387)	(0.0413)	(0.0387)	(0.0480)	(0.0599)	(0.0481)
RE Boom$^{\text{Small}}_{t-1}$ x Distance (t=0)	0.000120	0.000747	0.000132	-0.000788	0.000579	-0.000793
	(0.000443)	(0.000552)	(0.000442)	(0.000617)	(0.000867)	(0.000619)
RE Boom$^{\text{Small}}_{t-1}$ x Fr Closer Banks (t=0)		-0.459			-0.902*	
		(0.307)			(0.478)	
RE Boom$^{\text{Small}}_{t-1}$ x Fr More Profit Banks (t=0)			0.0515			0.197
			(0.168)			(0.200)
Observations	70,320	70,320	70,320	47,005	47,005	47,005
R-squared	0.934	0.934	0.934	0.939	0.939	0.939
Branch x Loan Area FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Area x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Market Concentration Level	All	All	All	Med/Low	Med/Low	Med/Low

Table 12: Low Income Propagation

The table replicates column (4) from Tables 7 and 8 and column (1) from Tables 7 and 8 using a subset of census tract groups with Low and Moderate-middle income. For more information about definitions refer to the original tables. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) SBL	(2) SBL	(3) SBL	(4) SBL
$\text{Fracking}^{\text{Small}}_{t-1}$	0.662***	0.687***	0.202**	0.232***
	(0.248)	(0.232)	(0.0861)	(0.0886)
$\text{Fracking}^{\text{Small}}_{t-1}$ x Distance		0.00257		-0.00137**
		(0.00343)		(0.000587)
$\text{Fracking}^{\text{Big}}_{t-1}$	0.0577	0.00815	-0.0148	-0.00410
	(0.0604)	(0.0732)	(0.0191)	(0.0246)
Observations	12,282	12,282	104,413	104,413
R-squared	0.871	0.871	0.905	0.905
Branch x Loan Area FE	Yes	Yes	Yes	Yes
Loan Area x Year FE	Yes	Yes	Yes	Yes
Income	Low	Low	Moderate-Middle	Moderate-Middle

VARIABLES	(1) SBL	(2) SBL	(3) SBL	(4) SBL
$\text{RE Boom}^{\text{Small}}_{t-1}$	0.151	-0.122	-0.0418	-0.0436
	(0.292)	(0.305)	(0.0464)	(0.0475)
$\text{RE Boom}^{\text{Small}}_{t-1}$ x Distance		-0.0132**		0.000164
		(0.00659)		(0.000689)
$\text{RE Boom}^{\text{Big}}_{t-1}$	0.147	0.207*	0.00705	-0.0443**
	(0.0971)	(0.110)	(0.0194)	(0.0222)
Observations	2,133	2,133	49,669	49,669
R-squared	0.929	0.929	0.934	0.934
Branch x Loan Area FE	Yes	Yes	Yes	Yes
Loan Area x Year FE	Yes	Yes	Yes	Yes
Income	Low	Low	Moderate-Middle	Moderate-Middle

Table 13: Robustness by Loan Size: Lending Competition

The table replicates column (7) from Tables 7 and 8 using a subset of small business loans with size below $.1M, in (1), and above $.25M, in (2), column (3) combines the two categories. For more information about definitions refer to the original tables. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) SBL<.1M	(2) SBL>.25M	(3) SBL<.1M >.25M
$\text{Fracking}^{\text{Small}}_{t-1}$	0.561**	0.159	1.071***
	(0.272)	(0.314)	(0.333)
$\text{Fracking}^{\text{Small}}_{t-1}$ x Distance	0.00170	-0.00136	-0.00772***
	(0.00350)	(0.00269)	(0.00255)
$\text{Fracking}^{\text{Small}}_{t-1}$ x Fr Closer Banks	3.586*	1.813	6.678***
	(1.971)	(2.258)	(2.076)
Distance	-0.0245***	-0.0112***	-0.0290***
	(0.00148)	(0.00157)	(0.00179)
Observations	44,617	30,014	48,142
R-squared	0.912	0.890	0.887
Branch x Census Tract Group FE	Yes	Yes	Yes
Census Tract Group x Year FE	Yes	Yes	Yes
Market Concentration Level	Med	Med	Med

VARIABLES	(1) SBL<.1M	(2) SBL>.25M	(3) SBL<.1M >.25M
RE $\text{Boom}^{\text{Small}}_{t-1}$	0.000675	-0.387***	-0.275***
	(0.0855)	(0.115)	(0.102)
RE $\text{Boom}^{\text{Small}}_{t-1}$ x Distance	0.000730	0.00172	0.000951
	(0.00120)	(0.00140)	(0.00117)
RE $\text{Boom}^{\text{Small}}_{t-1}$ x Fr Closer Banks	-0.0910	-1.995**	-1.354*
	(0.647)	(0.849)	(0.738)
Distance	-0.0194***	-0.00640***	-0.0232***
	(0.00140)	(0.00211)	(0.00173)
Observations	43,180	21,595	45,573
R-squared	0.946	0.924	0.933
Branch x Census Tract Group FE	Yes	Yes	Yes
Census Tract Group x Year FE	Yes	Yes	Yes
Market Concentration Level	Med/Low	Med/Low	Med/Low

Table 14: Robustness by Census Tract Income: Lending Competition

The table replicates column (3) from Tables 7 and 8 using a subset of census tract groups with moderate-middle income in column (1), and upper income bracket in column (2). For more information about definitions refer to the original tables. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) SBL	(2) SBL
$\text{Fracking}_{t-1}^{\text{Small}}$	0.317*	1.092***
	(0.173)	(0.278)
$\text{Fracking}_{t-1}^{\text{Small}}$ x Distance	-0.00191	-0.00495***
	(0.00126)	(0.00178)
$\text{Fracking}_{t-1}^{\text{Small}}$ x Fr Closer Banks	0.420	6.015***
	(1.363)	(1.853)
Distance	-0.0239***	-0.0370***
	(0.00129)	(0.00299)
Observations	66,640	22,968
R-squared	0.919	0.913
Branch x Census Tract Group FE	Yes	Yes
Census Tract Group x Year FE	Yes	Yes
Census Tract Group Income	Moderate-Middle	Upper

VARIABLES	(1) SBL	(2) SBL
RE $\text{Boom}_{t-1}^{\text{Small}}$	-0.186***	-0.389***
	(0.0704)	(0.138)
RE $\text{Boom}_{t-1}^{\text{Small}}$ x Distance	0.00141*	0.00170
	(0.000850)	(0.00131)
RE $\text{Boom}_{t-1}^{\text{Small}}$ x Fr Closer Banks	-1.164**	-1.401
	(0.532)	(1.012)
Distance	-0.0273***	-0.0345***
	(0.00163)	(0.00349)
Observations	40,441	15,876
R-squared	0.937	0.931
Branch x Census Tract Group FE	Yes	Yes
Census Tract Group x Year FE	Yes	Yes
Census Tract Group Income	Moderate-Middle	Upper

Figure 1: Distribution of Fracking Wells by Year

This figure shows the distribution of new oil wells by year. Well co-ordinates and the date of completion comes from surveys conducted by each state's department of natural resources.The information is aggregated by the sHomeland Infrastructure Foundation.

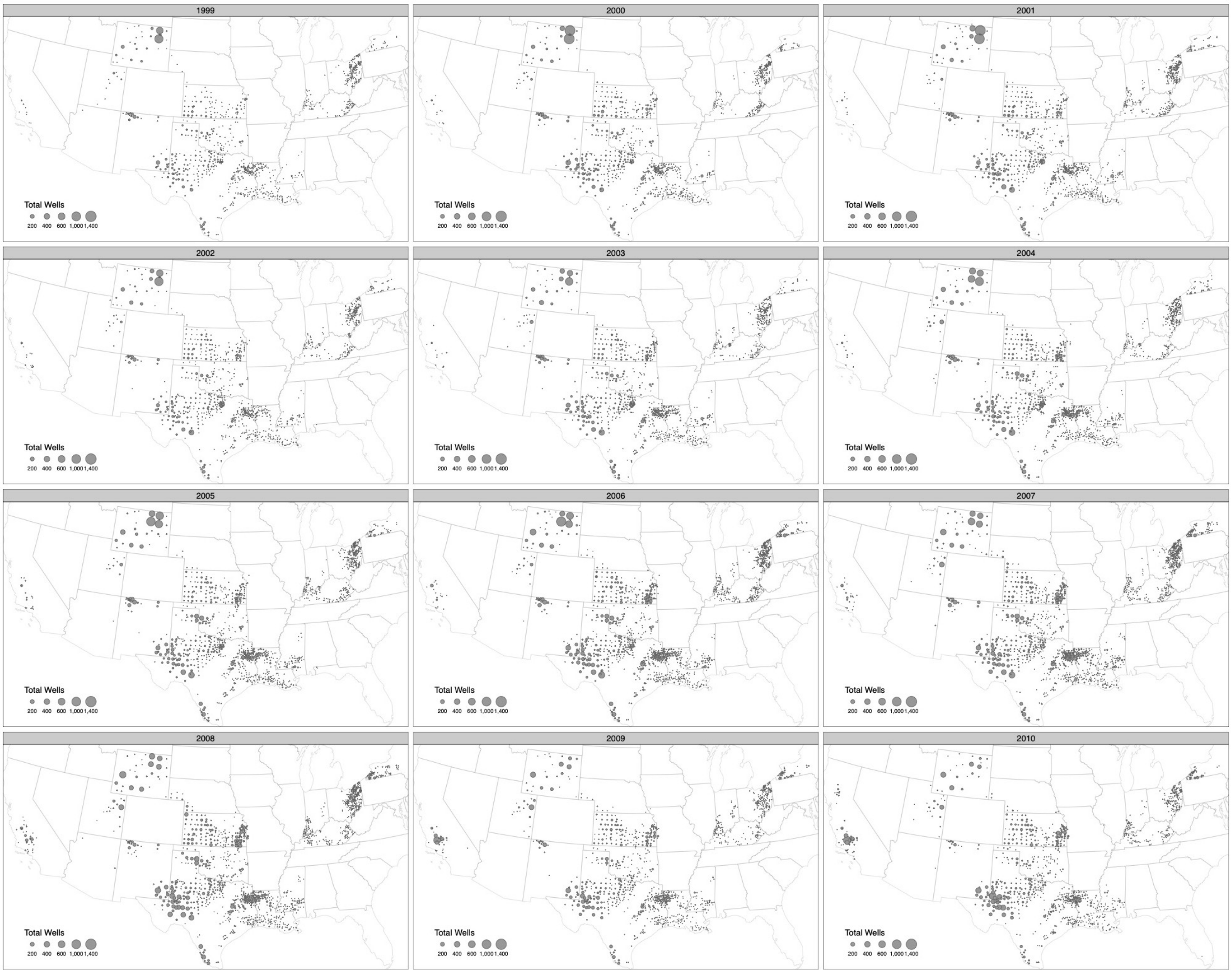


Figure 2: Annual Change in House Prices

This figure shows house price appreciation at distinct census tract for each year. The information is form FHFA using the growth rate of the HPI.

Figure 3: The Effect of Oil Boom Proximity on Deposit Growth: Small Banks

This figure compares the distribution of state-year branch average of deposit growth and bank deposit growth by treated status. I plot data for smaller banks for the entire fracking sample.

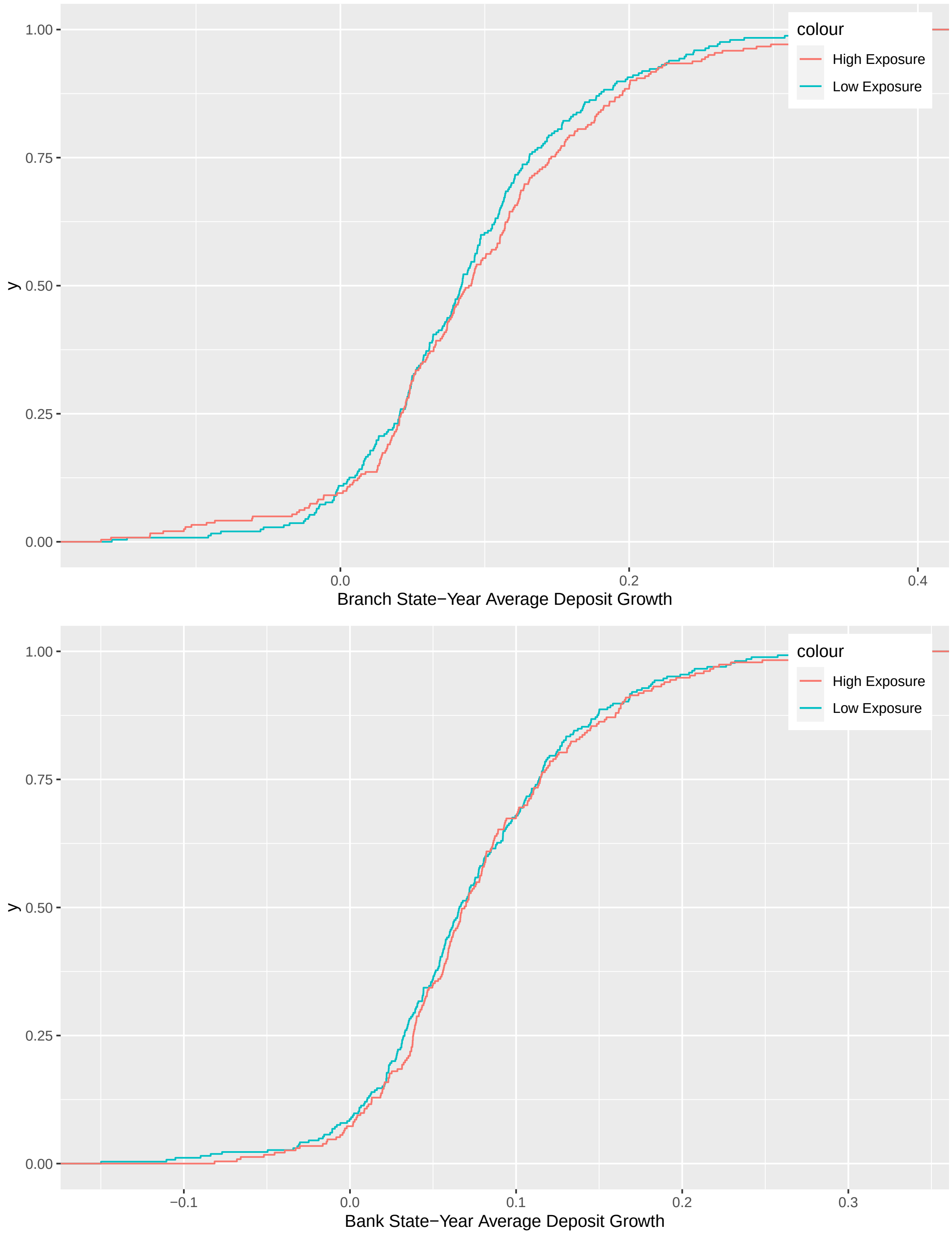
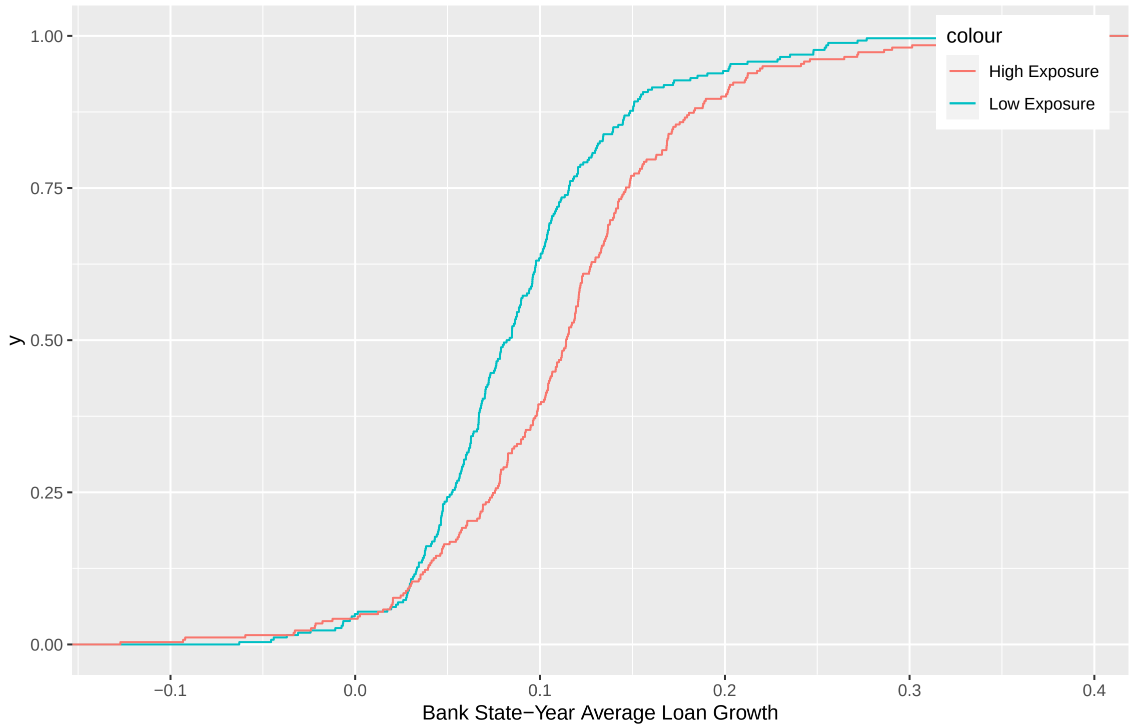


Figure 4: The Effect of Residential Boom Proximity on Loan Growth: Small Banks

This figure compares loan growth by exposure for small banks in the residential booms sample.



Appendix (for online publication)

Table A1: Robustness: Branch to Firm Distance

The table lists estimates from $\ln \text{SBL}_{i,j,m,t} = \alpha \ln \text{SBL}_{i,j,m,t-1} + \beta 1(\text{Boom})_{i,t} + \zeta X_{i,t-1} + \phi_{i,j,m} + \eta_{m,t} + \epsilon_{i,j,m,t}$. The table replicates the results from Tables 5 and 6 by changing the distance between the branch and the firm which is allowed in the sample. The main results focused on loans within 375 miles. Here I include loans within approximately 600 miles in column (1) and all loans in column (2). For additional details about notation, please consult Table 5. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) SBL	(2) SBL
$\text{Fracking}^{\text{Small}}_{t-1}$	0.181***	0.163**
	(0.0695)	(0.0667)
$\text{Fracking}^{\text{Big}}_{t-1}$	-0.0843***	-0.166***
	(0.0150)	(0.0134)
Observations	160,104	185,168
R-squared	0.908	0.917
Branch x Loan Area FE	Yes	Yes
Loan Area x Year FE	Yes	Yes
Small x Year FE	Yes	Yes
Distance from Fracking Over	60 miles	60 miles
Branch-Firm Distance	<600miles	All

VARIABLES	(1) SBL	(2) SBL
$\text{RE Boom}^{\text{Small}}_{t-1}$	-0.130***	-0.127***
	(0.0380)	(0.0360)
$\text{RE Boom}^{\text{Big}}_{t-1}$	0.0398**	0.0559***
	(0.0163)	(0.0155)
Observations	77,254	86,799
R-squared	0.939	0.943
Branch x Loan Area FE	Yes	Yes
Loan Area x Year FE	Yes	Yes
Small x Year FE	Yes	Yes
Loan Areas w HPI below	6pct	6pct
Branch-Firm Distance	<600 miles	All

Table A2: Robustness: Intermediate Size Banks

The table lists estimates from $\ln \text{SBL}_{i,j,m,t} = \alpha \ln \text{SBL}_{i,j,m,t-1} + \beta 1(\text{Boom})_{i,t} + \zeta X_{i,t-1} + \phi_{i,j,m} + \eta_{m,t} + \epsilon_{i,j,m,t}$. The table replicates the results from Tables 5 and 6 by separating out the effect of boom exposure for intermediately-sized banks. For additional details about notation, please consult Table 5. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) SBL
$\text{Fracking}^{\text{Small}}_{t-1}$	0.434***
	(0.0785)
$\text{Fracking}^{\text{Big}}_{t-1}$ (Asset<10B)	-0.202***
	(0.0395)
$\text{Fracking}^{\text{Big}}_{t-1}$ (Asset>10B)	0.0414**
	(0.0167)
Observations	150,547
R-squared	0.906
Branch x Loan Area FE	Yes
Loan Area x Year FE	Yes
Small x Year FE	Yes
Distance from Fracking Over	60 miles

VARIABLES	(1) SBL
RE $\text{Boom}^{\text{Small}}_{t-1}$	-0.118**
	(0.0506)
RE $\text{Boom}^{\text{Big}}_{t-1}$ (Asset<10B)	-0.0120
	(0.0336)
RE $\text{Boom}^{\text{Big}}_{t-1}$ (Asset>10B)	0.0205
	(0.0178)
Observations	70,320
R-squared	0.934
Branch x Loan Area FE	Yes
Loan Area x Year FE	Yes
Small x Year FE	Yes
Loan Areas w HPI below	6pct