Banking Market Structure and Local Access to Finance: Evidence from U.S. Oil and Natural Gas Shale Booms*

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Abstract

I use shale discoveries as a natural experiment to identify where and when local access to finance is economically important for firms. Shale discoveries create personal wealth windfalls, which cause an exogenous increase in bank deposits and a positive credit supply shock. After a credit supply shock, business establishments with high external finance requirements increase relative to those with low external finance requirements, but only in lending markets dominated by small banks. There is no effect in other lending markets. This suggests that local lending market characteristics are important in determining the effect of lending frictions on real outcomes.

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1 Introduction

In frictionless financial markets, entrepreneurs and firms should be able to obtain funding for all positive net present value projects. In such a world, changes in local credit supply would have no effect on real outcomes. However, if information or agency frictions interfere with capital mobility then suboptimal outcomes can occur. Existing empirical literature has focused on the real effects of these financing frictions.[1] Understanding exactly when and where these frictions are most important, however, has received much less attention.

There are reasons to believe that the importance of lending market frictions may vary, due to the substantial variation that exists across local lending markets. For example, some lending markets have large multi-market banks that can redeploy capital geographically (Gilje et al. (2013)), while other markets are dominated by small banks that rely on local sources of capital for lending (Houston et al. (1997), Kashyap and Stein (2000), Campello (2002)). Do these differences result in different exposures to lending market frictions? Do these differences have real effects? These questions have direct implications for our understanding of how real outcomes are affected by lending market frictions.

The goal of this study is to identify where and when lending market frictions have the largest influence on real outcomes by measuring the effect of *similar* changes in local credit supply on real outcomes in *different* lending markets. I use a novel source of exogenous variation in local credit supply from oil and natural gas shale discoveries to examine the effect of changes in credit supply on real outcomes. I identify shale discoveries ("booms") at the county level in the seven major shale producing U.S. states between 2003 and 2009 using a unique dataset of 16,731 individual shale wells. Unexpected technological breakthroughs in shale development have caused energy companies to make high payments to individual mineral owners for the right to develop shale discoveries. I find that the increase in individid-

[1] This literature includes Peek and Rosengren (2000), Petersen and Rajan (2002), Ashcraft (2005), Becker (2007), Khwaja and Mian (2008), Paravisini (2008), Agarwal and Hauswald (2010), Butler and Cornaggia (2011), Chava and Purnanandam (2011), Iyer and Peydro (2011), Schnabl (2011)

ual mineral wealth associated with shale booms raises local bank deposits by 9.3%. These deposits from newly wealthy mineral owners enhance a bank's ability to make new loans, resulting in a positive local credit supply shock.

To measure how a shale boom credit supply shock affects real outcomes in a lending market I use a difference-in-differences empirical specification to compare the number of business establishments, my outcome measure, before a boom to after a boom across industries with different external financing requirements.[2] Because both credit supply and credit demand may be changing in a shale boom I focus on within county-year comparisons. Specifically, to identify the causal effect of changes in credit supply I include county-year fixed effects, so that any demand effect which impacts industries similarly in a given county in a given year is controlled for.

I find that after a shale boom, the number of business establishments in industries with high external finance requirements increases 4.6% relative to industries with low external finance requirements.[3] More importantly, for the purposes of this study, this figure varies across different lending markets. I find that the effect of changes in credit supply on local firms is strongly linked with local banking market structure, with areas dominated by small banks benefiting the most from an expansion in local credit supply. Specifically, after a boom the number of business establishments in industries with high external finance requirements increases 7.1% relative to the number with low external finance requirements in counties dominated by small banks, whereas there is no change in other lending markets. This result indicates that cross sectional variation in the impact of credit supply frictions on real outcomes is linked with a lending market's banking structure.

Why might local credit supply be particularly important in counties dominated by small

[2] A business establishment is an operating address of a firm; a single firm may have multiple business establishments. I use this as my primary outcome measure as it is among the most granular economic data available at the county-year-industry level during the sample period.

[3] I have excluded all economic outcome measures directly related to oil and gas extraction, construction, real estate, and financial services, because economic outcomes for these industries potentially improve due to reasons unrelated to better local credit supply.

banks? If local banks are large, capital can be redeployed geographically to fund projects. However, if local banks are small it could be more difficult for capital to be redeployed from other areas to be lent locally.[4] Furthermore, small banks are typically more reliant on deposit funding than large banks, which suggests they may have more challenges in obtaining alternative external capital due to information and agency concerns. Prior research also suggests that small banks may be more adept at lending to “soft” information borrowers (Stein (2002), Berger et al. (2005)). If areas with more small banks have more “soft” information borrowers, the inability of a small bank to obtain outside funding for these types of borrowers would also lead to worse economic outcomes. The results of this paper indicate that the ultimate set of information and agency frictions influencing outcomes are both frictions between borrowers and banks as well as frictions between banks and funding sources.

Non-credit based interpretations of my results may be a concern.[5] For example, some industries could benefit differentially from a shale discovery due to consumer demand shocks, wealth shocks, or other non-credit based shocks associated with a shale discovery. If any of these shocks are correlated with external financing requirements, then a credit supply based interpretation of the results could be problematic. However, for these alternative shocks to alter the interpretation of my empirical design, they would also need to be correlated with the size of a county’s local banks. I find no evidence that after booms demand shocks differ across counties with different bank sizes. Specifically, retail sales, a proxy for local demand, increase by similar amounts after booms in counties dominated by small banks as they do in other counties. Additionally, there is no evidence that deposits increase more after booms in counties dominated by small banks than in other counties, as one might expect if demand shocks affected counties differently. More broadly, the empirical design of this

[4]Prior research discussing this issue includes Houston et al. (1997) and Jayaratne and Morgan (2000)

[5]I follow the approach of other studies and focus on economic outcome variables, because detailed bank level loan data is typically unavailable in the United States. Among banks which have all of their branches in a shale boom county, which plausibly suggests that a significant portion of the lending activity reported in Call Report disclosures occurs in a shale county, I do confirm that Commercial and Industrial loans increase after a shale discovery.

paper requires an alternative, non-banking based, interpretation of results to reconcile why outcomes for industries with distinct external financing requirements respond differently after a shale boom, and why these different responses are larger in counties dominated by small banks.

In placebo tests I show that the results of this study are not driven by pre-existing growth trends. I also demonstrate that the main results of this study are not driven by any single industry or industry exposure to economic fluctuations as proxied by industry asset beta. Additionally, I conduct robustness tests related to local banking structure and find that my main results are not driven by changes to local banking markets after a boom, different small bank size definitions, or banks that are part of holding companies.

How are shale booms different than other types of economic growth? I argue that the key differentiator of shale booms is the significant relative increase in local credit supply in shale counties, relative to other types of growth shocks. Because county banking market structure is not randomly assigned, a concern may be that the real outcomes I observe are not driven by a deposit effect, but instead, an omitted variable which affects how certain counties or certain industries respond to economic growth (e.g. rural and underdeveloped areas may respond differently when there is growth). To attempt to identify how this might be influencing my tests, I examine whether non-shale growth shocks affect counties dominated by small banks differently or firms with greater external financing requirements differently. I find no evidence of differential affects linked to county banking market composition or industry external financing requirements in response to non-shale growth shocks. This result is consistent with the credit supply component of shale booms being a key factor for real outcomes, relative to other types of economic growth.

Are banks using shale deposit windfalls to fund positive net present value projects? While difficult to test empirically, there are at least two pieces of suggestive evidence which indicate that banks are not making bad loans. First, an analysis of banks which have all of their operations in shale counties, for which Call Report data may be considered plausibly representative of the loans a bank may be making in a shale county, I find no evidence that a bank's non-performing loan ratio increases after a shale boom. Second, establishments in industries with high external finance requirements represent a smaller portion of the economy in lending markets dominated by small banks. Specifically, in non-shale counties dominated by small banks they comprise 37.8% of all establishments in 2009. In lending markets dominated by small banks that have benefited from a shale boom, this figure is 40.8%. This amount is nearly equal to the 40.7% they comprise in lending markets with a greater presence of large banks. Thus, these additional establishments increase only to an amount similar to their proportion in counties with a greater presence of large banks, the control group, they are not increasing to a level significantly higher than the control group, which might be a cause for concern.

One should be cautioned against interpreting the results of this study as suggesting that the existence of small banks is suboptimal. Due to the type of borrowers small banks may serve, and the potential difference in borrowers in counties dominated by small banks relative to other counties, it is not clear that more big banks would improve outcomes. Alternatively, this study does suggest that improved access to funding in areas dominated by small banks does lead to improved outcomes. The results would suggest that additional tools or innovations which could mitigate information or agency frictions for small banks in obtaining funding, may improve outcomes in areas dominated by small banks.

This study also highlights a bright side, linked to the limited impact of frictions in some lending markets, as areas with a significant presence of large banks are largely unaffected by changes in local credit supply. This suggests that some economically important lending frictions in some places have been mitigated, relative to what prior studies have found (Becker (2007), Peek and Rosengren (2000)).

In Section 2 I provide an overview of the hypothesis tested in this study and the related literature. Section 3 provides detail on my identification strategy and background on my natural experiment. Section 4 discusses data and variable definitions. Section 5 discusses my results, and Section 6 concludes the paper.

2 Hypothesis Development and Related Literature

The underlying empirical design of this paper is a dual hypothesis test of two sets of frictions 1) frictions between borrowers and banks 2) frictions between banks and access to funds for lending. Both sets of frictions have to be present for the observed results.

If firms could seamlessly access capital regardless of location, then neither local credit supply, local banking characteristics, nor a local bank's ability to obtain external funds for lending would matter for local economic outcomes. Any local negative credit shock would be counteracted by distant lenders stepping in to fund positive net present value projects. Recent research suggests that geography and distance currently play less of a role in enhancing informational frictions between borrowers and banks due to improved use of information technology. Berger (2003) documents the rise of internet banking, electronic payment technologies, and credit scoring, while Loutskina and Strahan (2009) document the importance of securitization. These advances would suggest a reduced importance of local access to finance, because borrowers can more easily convey information about themselves to banks that are farther away.

Regulatory based frictions in the U.S. have also eroded over time, reducing the importance of distance in lending relationships. Banking deregulation in U.S. states has affected output growth rates (Jayaratne and Strahan (1996)), the rate of new incorporations (Black and Strahan (2002)), the number of firms and firm-size distribution (Cetorelli and Strahan (2006)), and entrepreneurship (Kerr and Nanda (2009)). Additionally, Bertrand et al. (2007) document that banking deregulation in France leads to better allocation of bank loans to firms and more restructuring activity.

If distance does aggravate information based frictions between borrowers and lenders, then local credit supply may matter. In particular, if the cost to overcoming distance related frictions is prohibitive as could be the case with "soft" information borrowers[6], then local credit supply could be important. In this setting, the frictions that a bank faces in obtaining external funding become important for local economic outcomes. Existing literature suggests that bank size is a key characteristic along which frictions in obtaining external capital may vary. Kashyap and Stein (2000) document that monetary policy influences lending for small banks more than for large banks, while Bassett and Brady (2002) document that small banks rely more on deposit funding. Smaller banks also have fewer sources of funding outside a local area (Houston et al. (1997), Jayaratne and Morgan (2000), Campello (2002)). If small banks need to raise capital externally, while large banks can redeploy capital internally across different geographic regions, then areas with more small banks may have more agency and informational frictions related to obtaining external funding. These bank funding frictions may mean that areas with a higher proportion of small banks could be less likely to have access to funding beyond local deposits.

This paper is also more broadly related to other papers which document the importance of access to finance for economic outcomes in different settings earlier in the United States (Peek and Rosengren (2000), Ashcraft (2005), Chava and Purnanandam (2011), Samila and Sorenson (2011), Adelino et al. (2014)) and internationally (Khwaja and Mian (2008), Iyer and Peydro (2011), Schnabl (2011), Paravisini (2008), Pascali (forthcoming)). In other related work, Guiso et al. (2004) use Italian data to document the importance of financial development on new firm entry, competition, and growth. Recent literature has also used natural experiments in the U.S. to document the importance of local access to finance for

[6]Small banks may focus more on relationship lending based on "soft" information relative to transaction lending (Berger and Udell (2006)). Sufi (2007) documents that borrowers and lenders are geographically close when information asymmetry is severe.

productivity (Butler and Cornaggia (2011)) and risk-management (Cornaggia (2012)). Additionally, Plosser (2011) uses shale discoveries as an instrument for bank deposits, but focuses on bank capital allocation decisions during financial crises. My contribution differs from these papers in that I identify significant cross-sectional variation in the effect of changes in local credit supply on firms. Characterizing this variation provides insight as to where and when information and agency frictions affect the flow of capital in the banking system and have the largest impact on firms.

3 Identification Strategy: Shale Discoveries

3.1 Natural Gas Shale Industry Background

The advent of natural gas shale development is one of the single biggest changes in the U.S. energy landscape in the last 20 years. According to the U.S. Energy Information Agency, in its 2011 Annual Energy Outlook, there are 827 Trillion Cubic Feet (Tcf) of technically recoverable unproved shale gas reserves in the United States, this estimate is a 72% upward revision from the previous year. 827 Tcf of natural gas is enough to fulfill all of the United States' natural gas consumption for 36 years. On an energy equivalent basis 827 Tcf represents 20 years of total U.S. oil consumption or 42 years of U.S. motor gasoline consumption. As recently as the late 1990s, these reserves were not thought to be economically profitable to develop, and represented less than 1% of U.S. natural gas production. However, the development of the first major natural gas shale "play" in the United States, the Barnett Shale in and around Fort Worth, TX, changed industry notions on the viability of natural gas shale.

In the early 1980s Mitchell Energy drilled the first well in the Barnett Shale (Yergin (2011)). However, rather than encountering the typical, highly porous, rock of conventional formations, Mitchell encountered natural gas shale. Shale has the potential to hold vast amounts of gas, however, it is highly non-porous which causes the gas to be trapped in the rock. Over a period of 20 years Mitchell Energy experimented with different techniques, and found that by using hydraulic fracturing (commonly referred to as "fracking") it was able to break apart the rock to free natural gas. With higher natural gas prices and the combination of horizontal drilling with "fracking" in 2002, large new reserves from shale became economically profitable to produce. Continued development of drilling and hydraulic fracturing techniques have enabled even more production efficiencies, and today shale wells have an extremely low risk of being unproductive (unproductive wells are commonly referred to as "dry-holes").

The low risk of dry-holes and high production rates have led to a land grab for mineral leases which were previously passed over. Prior to initiating drilling activities a firm must first negotiate with a mineral owner to lease the right to develop minerals. Typically these contracts are comprised of a large upfront "bonus" payment, which is paid whether the well is productive or not, and a royalty percentage based on the value of the gas produced over time. Across the U.S., communities have experienced significant fast-paced mineral booms. For example, the New Orleans' *Times-Picayune (2008)* reports the rise of bonus payments in the Haynesville Shale, which increased from a few hundred dollars an acre to $10,000 to $30,000 an acre plus 25% royalty in a matter of a year. An individual who owns one square mile of land (640 acres) and leases out his minerals at $30,000/acre would receive an upfront one-time payment of $19.2 million plus a monthly payment equal to 25% of the value of all the gas produced on his lease.[7] The media has dubbed those lucky enough to have been sitting on shale mineral leases as "shalionaires." The significant personal windfalls people have experienced in natural gas shale booms has led to increases in bank deposits in the communities that they live in. Since the first major shale boom in the Barnett (TX), additional booms have occurred in the Woodford (OK), Fayetteville (AR), Haynesville (LA + TX), Marcellus (PA + WV), Bakken (Oil ND), and Eagle Ford (TX).

[7]The size and scale of these payments distinguish these events from other types of economic growth, as well as other types of natural resource extraction (Glaeser et al. (forthcoming), for example).

3.2 Identification Strategy

The booms experienced by communities across the U.S. due to shale discoveries are exogenous to the underlying characteristics of the affected communities (health, education, demographics etc). The exogenous factors driving shale development include technological breakthroughs (horizontal drilling/hydraulic fracturing) and larger macroeconomic forces (demand for natural gas and natural gas prices). Acknowledging the unexpected nature of shale gas development John Watson, CEO of Chevron, stated in a *Wall Street Journal (2011)* interview, that the technological advances associated with "fracking" took the industry "by surprise." The development of shale discoveries is typically undertaken by large publicly traded exploration and production companies that obtain financing from financial markets outside of the local area of the discovery. To track shale development I use a unique data set which has detailed information on the time and place (county-year) of drilling activity associated with shale booms.[8] The exogenous nature of a shale boom and the effect it has on local deposit supply creates an attractive setting for a natural experiment, which I use to identify the importance of local credit supply and local banking market structure.

3.2.1 Effect of Boom on Deposits

The first step in my analysis is to quantify the deposit shock in shale boom counties. Specifically what is the impact of a shale boom on local deposit supply? In order to do this I estimate the following regression model

$$Deposit_{i,t} = \alpha + \beta_1 Boom_{i,t} + Year\ FE_t + County\ FE_i + \varepsilon_{i,t}$$

[8] I use horizontal wells as my key measure of shale development activity. Horizontal drilling is a component of the key technological breakthrough that enables the production of shale resources to be economically profitable. Nearly all horizontal wells in the U.S. are drilled to develop shale or other unconventional oil and gas resources.

$Boom_{i,t}$ is a measure of shale activity, in my tests I use both logarithm of total shale wells, and a binary dummy boom variable to measure the shale boom. $Deposit_{i,t}$ is either the logarithm of deposits summed across all branches in county i at time t or the logarithm of deposits per capita summed across all branches in county i at time t. County fixed effects are included to control for time invariant county effects and year effects are included to account for time-varying effects, these enter the specification in the form of $Year\ FE_t$ (year fixed effect) and $County FE_i$ (county fixed effect). The key variable of interest in this specification is the coefficient β_1, which indicates the change in $Deposit_{i,t}$ attributable to the $Boom_{i,t}$ variable.

A primary concern in my empirical setting may be whether counties with different bank size characteristics experience similar shocks. If a deposit shock were correlated with the underlying banking structure in a county it could suggest problems for my broader empirical tests. To test whether counties with different banking characteristics are affected differently by the deposit shock, I estimate the following regression:

$$Deposit_{i,t} = \alpha + \beta_1 Boom_{i,t} + \beta_2 Small\ Bank_{i,t}$$
$$+\beta_3 Small\ Bank_{i,t} * Boom_{i,t} + Small\ Bank_{i,t} * Year\ FE_t + County\ FE_i + \varepsilon_{i,t}$$

The key coefficient of interest in measuring whether counties with different bank size characteristics experience different deposit shocks is the interaction coefficient (β_3). This specification includes both $Small\ Bank_{i,t} * Year\ FE_t$ to control for differing deposit trends across counties with different banking structures and $County\ FE_i$ to control for time invariant county effects on deposit levels.

3.2.2 Effect of a Change in Credit Supply on Firms: Difference-in-Differences

To identify the economic outcomes related to the local credit supply shock, I use a regression specification which distinguishes between economic outcomes for industries with high external financing requirements relative to those with low external financing requirements. To achieve this aim, I use a regression form of difference-in-differences, where the first difference (β_1) can be thought of as the difference in economic outcomes between boom county-years and non-boom county-years. To identify the effect of the credit component of a boom I incorporate a second difference (β_3), the difference in economic outcomes for industries with high external finance requirements and industries with low external finance requirements.

$$Establishments_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + \beta_2 High_j + \beta_3 Boom_{i,t} * High_j$$
$$+ IndustryYear\ FE_{j,t} + CountyIndustry\ FE_{i,j} + CountyYear\ FE_{i,t} + \varepsilon_{i,j,t}$$

Where $Establishment_{i,j,t}$ is either the logarithm of the number of establishments in county i and industry group j at time t or the establishments per capita in county i and industry group j at time t. I have grouped establishments into two industry types: one industry group which has high requirements for external finance, for which $High_j = 1$ and one industry group with low requirements for external finance $High_j = 0$.[9] Thus, for every county I have two industry groups, which are delineated by requirements for external finance. I also include three sets of fixed effects. $IndustryYear\, FE_{j,t}$ control for time-varying differences in industry growth, $CountyIndustry\ FE_{i,j}$ control for county specific differences in industry make-up, while $CountyYear\, FE_{i,t}$ absorbs any county-year specific effects (e.g. demand effects) which might effect firms in both industry groups similarly.

[9] $High_j$ is not reported in the regression results because this variable is subsumed by the county-industry fixed effects, $CountyIndustry\ FE_{i,j}$, while $Boom_{i,t}$ is not reported because it is absorbed by $CountyYear\ FE_{i,t}$. The high dimensional fixed effects used for this study are based off of the techniques outlined in Gormley and Matsa (forthcoming)

This specification is a regression form of difference-in-differences, with the key variable of interest being the coefficient on the interaction term, β_3. If industries with a high dependence on external finance benefit more from shale booms, β_3 would be positive, which would indicate the importance of the credit supply component of a boom. Alternatively, if local credit supply does not influence local economic outcomes, β_3 would be zero. That is, while the boom may benefit all industries through the coefficient β_1 (overall increased demand for goods and services), there would be no evidence that the credit supply component of a boom enhances local economic outcomes.

3.2.3 Effect of Bank Size and Credit Supply on Firms: Triple Differencing

To estimate the importance of local bank size for local credit supply I use a triple differencing specification. The first two differences are: non-boom county-years vs. boom county-years, high requirements for external finance vs. low requirements for external finance. The third difference tests whether the effect from the first two differences is bigger in areas dominated by small banks: high small bank market share vs. low small bank market share. $Small\,Bank_{i,t}$ is a variable representing small bank market share in county i at time t. To measure small bank market share, $Small\,Bank_{i,t}$, I use both the proportion of branches in a county which belong to small banks as well as a dummy variable for the counties which are above median in small bank branch market share in any given year. The interaction of $Small\,Bank_{i,t}$ with the other terms in the specification yields a regression form of difference-in-difference-in-differences.[10]

[10] $High_j$ is not reported in the regression results because this variable is subsumed by the county-industry fixed effects, $CountyIndustry\ FE_{i,j}$, while $Boom_{i,t}$, $Small\ Bank_{i,t}$, and $Boom_{i,t} * Small\ Bank_{i,t}$ are not reported because they are absorbed by $CountyYear\ FE_{i,t}$

$$Establishments_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + \beta_2 High_j + \beta_3 Small\ Bank_{i,t}$$
$$+\beta_4 Boom_{i,t} * High_j + \beta_5 Boom_{i,t} * Small\ Bank_{i,t} + \beta_6 High_j * Small\ Bank_{i,t}$$
$$+\beta_7 Boom_{i,t} * Small\ Bank_{i,t} * High_j + IndustryTrends\ FE_{j,t}$$
$$+CountyIndustry\ FE_{i,j} + CountyYear\ FE_{i,t} + \varepsilon_{i,j,t}$$

In this regression the key variable of interest is β_7. If industries with higher requirements for external finance benefit more from a local credit supply shock in counties dominated by small banks this coefficient would be positive.

4 Data and Variable Definition

For my panel data set I include the seven states that have experienced shale development activity from 2000 through 2009. These are Arkansas, Louisiana, North Dakota, Oklahoma, Pennsylvania, Texas, and West Virginia. There are 639 counties in these states with at least one bank branch over the sample period. This sample includes counties that have experienced shale booms, as well as counties which have not, and it is these non-boom county-years which serve as a control group in empirical tests. The data is constructed on an annual frequency and compiled from four different sources:

- Well Data (From Smith International Inc.)
- Deposit and Bank Data (From FDIC Summary of Deposits Reports)
- County Level Economic Outcome Data by Industry (Census Bureau, Establishment Data)

- External Finance Requirement Measures (From Compustat)

4.1 Well Data

Well data is used to calculate the $Boom_{i,t}$ variables in the regressions. The well data is obtained from Smith International Inc. which provides detailed information on the time (year), place (county), and type (horizontal or vertical) of well drilling activity. I use horizontal wells as the key measure of shale development activity, as the majority of horizontal wells in the U.S. drilled after 2002 target shale or other unconventional formations. In order to best measure the influence of shale development activity I focus on two different measures.

- $Boom_{i,t} = Dummy_{i,t}$: A dummy variable set to 1 if county i at time t is in the top quartile of all county-years with shale well activity (total shale wells > 17) in the panel dataset. Once the variable is set to 1, all subsequent years in the panel for the county are set to 1. Based on this definition 88.1% of all shale wells are drilled in boom county-years.

- $Boom_{i,t} = Log\, Total\, Shale\, Wells_{i,t}$: The logarithm of the total number of shale wells drilled in county i from 2003 to time t.

Regressions are based on the total shale wells drilled for the year leading up through March. This corresponds to when the County Business Pattern Data are tabulated. Summary statistics on sample states, counties, and well data are presented in Table 1 as well as a detailed list of the shale boom counties used in this study. Figure 1 presents a map of the intensity and location of shale development activity.

4.2 Deposit and Bank Data

Deposit and bank data are obtained from the Federal Deposit Insurance Corporation (FDIC) Summary of Deposit data, which is reported on June 30 of each year and provides bank data for all FDIC-insured institutions. I use the Summary of Deposit data as opposed to data from the Reports of Condition and Income (Call Reports) because Summary of Deposit data provides deposit data at the branch level, while Call Reports only provide data at the bank level. Additionally, Summary of Deposit data provides detailed information on the geographic location of each branch that a bank has, so I can directly observe the branches in boom counties and the banks they belong to. To obtain county level deposit data I sum deposits across all branches in a county. To calculate small bank market share in a county I calculate the proportion of branches in a county which belong to small banks. I define small banks to be banks with assets below a threshold which could cause a bank to be funding constrained. For the results in this paper I use $500 million (year 2003 dollars) as the asset threshold for small banks.[11] Prior literature (Black and Strahan (2002), Jayaratne and Morgan (2000), Strahan and Weston (1998)), has suggested that banks with assets in the $100 million to $500 million range may be funding constrained. In my empirical tests I use two measures of small bank market share. Specifically, I use dummy variables set to 1 for the counties with high small bank branch market share (above median) in each year, and 0 otherwise. Additionally, I also use the ratio of small bank branches to total branches in a county. Summary data for bank and branch variables are provided in Table 2.

[11] I document that the main results remain statistically significant when using $200 million or $1 billion in assets as the definition of a small bank. The results are also robust to basing this definition on bank holding company assets.

4.3 County Level Economic Outcome Data by Industry

Economic outcome variable data by industry was obtained from the County Business Patterns survey, which is released annually by the Census Bureau. It is worth noting, that the survey provides data only at the establishment level, not the firm level, for example, a firm may have many establishments. The survey provides detailed data on establishments and employment in each county, by North American Industry Classification System (NAICS) code as of the week of March 12 every year. My main results are based on economic outcomes grouped at the two digit NAICS code level, which I match with corresponding Compustat two digit NAICS code external finance requirement measures. More disaggregated NAICS codes (six digit NAICS as opposed to two digit NAICS) provide fewer NAICS code matches to Compustat, which I rely on for external finance requirement measures. I exclude codes 21 (Oil and Gas Extraction), 23 (Construction), 52 (Financials), 53 (Real Estate) because they may be directly influenced by booms. I exclude 99 (Other) due to lack of comparability with Compustat firms.[12]

After matching County Business Pattern data with Compustat external finance requirement measures, I aggregate all industry codes into two industry groups, one with above median requirements for external finance (high) and one with below median requirements for external finance (low). The two digit NAICS code from the County Business Patterns data is used to obtain an external finance requirement measure from Compustat, which is described in more detail in the next subsection. The objective of the matching is to have the cleanest sorting of NAICS codes into high external finance requirement and low external finance requirement bins. Details on the industries in these bins are provided in Table 3.

While the County Business Patterns Survey provides detailed data on establishment

[12]Using three digit NAICS code industries poses two problems 1) There are 71 industries as opposed to 14, so there are far fewer comparable Compustat firms for some industries 2) There was a change in industry categorization that occurred in 2002-2003, which creates problems when constructing a pre-boom control period for booms that occur in 2003 and 2004.

counts by industry, employment data may be suppressed, for privacy reasons, if there are too few establishments in a particular industry. Employment data suppression is a particular problem for counties with smaller populations, for this reason the number of observations in employment regressions is reduced. Furthermore, this suppression of employment data makes including employment in the regressions related to small bank market share problematic, as 62% of establishments in high small bank market share counties have employment reporting suppressed, therefore I do not include employment as an outcome variable in my study.

4.4 External Finance Requirement Measures

I use an external finance requirement measure similar to the measure used by Rajan and Zingales (1998). The main difference is that while they use this measure only for manufacturing firms, I use it for all industry groups similar to Becker (2007). Specifically, over the 1999 to 2008 time period for each firm in Compustat I sum the difference between capital expenditures and operating cash flow. I use the time period 1999 to 2008 because these fiscal years, which end in December for most public firms, correspond most closely to March of the following year (2000 to 2009), which is when the county business patterns survey is conducted. By summing over several years the measure is less susceptible to being driven by short term economic fluctuations. I then divide this sum by the sum of capital expenditures. Specifically, for firm n, the measure is calculated as:

$$ExtFinRequirement_n = \frac{\sum_{1999}^{2008}(CapitalExpenditures_{n,t} - OperatingCashFlow_{n,t})}{\sum_{1999}^{2008} CapitalExpenditures_{n,t}}$$

I take the median of this measure to get an industry's external finance requirement. The calculation of this measure for each industry is displayed in Table 3. The underlying assumption in the Rajan and Zingales (1998) measure is that some industries, for technological reasons, have greater requirements for external financing than others. As Cetorelli and Strahan (2006) highlight, using a measure based on Compustat firms may be considered a cleaner measure, relative to the actual loan amounts small private firms may issue, of the true demand for financing of the firms in the sample. The measure is based on public firms in the United States which have among the best access to capital of any firms in the world, therefore the amount of capital used by these firms is likely to be a good measure of an industry's true demand for external financing. Cetorelli and Strahan (2006) further document a correlation between external finance requirement measures constructed from Compustat and those constructed from the Survey of Small Business Finance, providing further support for the use of this measure.

5 Results

5.1 Effect of Shale Booms on Deposit Levels

Table 4 provides regression results of log deposits and log deposits per capita on different shale boom variables. The evidence suggests a causal relationship between shale booms and bank deposits, specifically, that the individual mineral wealth generated by shale booms translates into more bank deposits. In Panel A of Table 4 columns (1) and (2) provide results on different measures of the $Boom_{i,t}$ variable. In each case, the $Boom_{i,t}$ variable is found to have both economic and statistical significance. For example, the dummy variable measure of $Boom_{i,t}$ can be interpreted as a boom increasing local deposits by 9.3%. To put this in context, the average annual growth rate in deposits across all counties from 2000 to 2009 was 4.6%, so a boom county would experience an additional increase of 9.3% (4.6% + 9.3% = 13.9% total increase), or a total increase in deposits roughly triple its average annual increase.

Further tests will focus on comparisons between counties with high small bank market share and low small bank market share. An assumption in this comparison is that both types of counties experience similar deposit shocks. To directly test this assumption I estimate interactions of county bank size characteristics interacted with the shale boom variables. Panel B reports the results of this specification. The key coefficient of interest in assessing whether counties experience different shocks based on their banking structure is the coefficient on the interaction term (β_3). This coefficient is neither economically nor statistically significant, suggesting that counties with different banking structures receive similar deposit shocks.

An additional concern may be that deposits could be rising in anticipation of a boom, or that there could be some spurious correlation in a county during part of the boom period which is causing the result in Table 4. To test the precise timing of the boom relative to deposit growth I replace the boom dummy variable used in Table 4 with dummy variables based on the position of an observation relative to a boom. So, for example, if a boom occurs in 2006 in county i, then the observation in county i in 2003 would receive a t-3 boom dummy, county i observation in 2004 would receive the t-2 boom dummy and so on. I include a set of dummies for each year relative to a boom from t-3 to t+3. Due to limited observations beyond t+3, I group any observations after t+3 with the t+3 dummy (3+). Figure 2 is a graph of the coefficients from this regression, and provides visual evidence that the deposit level does not change substantially until time 0, the first year of the boom. This serves to alleviate concerns regarding whether deposits rise in anticipation of a boom, as well as concerns about possible spurious correlations during part of the boom period.

5.2 Effect of Credit Supply Shock on Firms

In order to estimate the effect of the credit supply shock associated with a shale boom on firms, it is necessary to look at the difference between outcomes for firms in industries with a high requirement for external finance compared to those with a low requirement for external finance. To measure the credit supply effect of a boom, I not only compare firms in different industries, but also include county-year fixed effects in regression specifications, therefore any direct demand effect that both industry groups experience is fully absorbed. Table 5 provides a direct estimate of the effect of the credit supply shock on firms using a regression form of difference-in-differences. The coefficient of interest for assessing whether improved local credit supply plays a role in local economic outcomes is the interaction term $Boom_{i,t} * High_j$. The sign and magnitude of this term indicates whether one industry group is affected disproportionately when there is a credit supply shock. The coefficient on the interaction term is positive and statistically significant in all specifications, suggesting that firms in industries with high external finance requirements benefit more than firms in industries with low external finance requirements. The outcome measures used in the regressions are logarithm of the number of establishments and establishments per capita in each industry group. The economic interpretation of the interaction coefficient in (1) of Table 5 is that, when there is a boom, establishments in industries with high requirements for external finance increase 4.6% relative to establishments in industries with low requirements for external finance. To put this number in context, the average annual increase in establishments of firms in industries with high external finance requirements from 2000 to 2009 is 0.9%. The interpretation of (3) in Table 5 is that there are 3.6 additional establishments per 10,000 people after the credit supply shock in industries with high external finance requirements relative to industries with low external finance requirements. [13]

There may be some concern as to the timing of the boom and changes in local economic outcomes. If establishment levels of low external finance requirement industries and high external finance requirement industries trend differently prior to the boom, they may be poor control/treatment groups. Additionally, if high external finance requirement establishments trend higher well before the boom, it would suggest a problem with my empirical design, as

[13] I document in Appendix A that for banks that have all branches in a single county, both deposits and Commercial & Industrial loans increase after a boom. Overall interest income and interest paid on deposits are unchanged after a boom. Lending driven purely by demand would be more likely to result in higher interest rates and interest income.

the deposit levels in Figure 2 do not increase until time 0. To directly assess the validity of these concerns I construct a graph similar to Figure 2, but for establishments. Specifically, for each of the industry groups I estimate a regression, but replace the $Boom_{i,t}$ variable with a set of dummy variables based on the time period of an observation relative to a boom for any given county i (similar to what is done in Figure 2). The coefficients from this regression are graphed for each industry group in Figure 3. As can be seen, from time t-3 to t-1, each industry group tracks relatively closely, then at time 0, the first year of a boom, there is a divergence in trends, which increases through t+3. This indicates that when the boom occurs, establishments in high external finance requirement industries benefit disproportionately more compared to low external finance requirement industries. The evidence presented in Figure 3 should serve to address concerns regarding the change in establishment levels relative to the precise timing of a boom.

5.3 Effect of Bank Size and Credit Supply on Firms

As previously discussed, local bank size composition could play a role in the importance of improved local credit supply for economic outcomes. Specifically, counties dominated by small banks may benefit more from a credit supply shock due to information and agency frictions in the banking system. To test this in a difference-in-differences framework, I subdivide counties into high small bank market share and low small bank market share counties, based on whether a county is above median in small bank market share in a given year. I estimate the specification presented in Table 5 for each of these subgroups, and report the results in Table 6.

In every specification the counties dominated by small banks have a higher coefficient for the interaction term $Boom_{i,t} * High_j$. The magnitude of the difference is often quite large, with high small bank market share counties (Bank = High Small Bank Mkt Share) having coefficients four to five times higher than the coefficients of low small bank market share counties (Bank = Low Small Bank Mkt Share), depending on the specification. The interaction coefficient for lending markets with low small bank market share is often not statistically significant. The economic interpretation of (1) is that establishments in industries with high requirements for external finance increase 7.1% relative to establishments in industries with low requirements for external finance after a shale boom. While the economic interpretation of (2) is that establishments in industries with high requirements for external finance increase 1.2% relative to establishments in industries with low requirements for external finance, though this difference is not statistically significant. These results indicate that there is significant cross-sectional variation in the effect of changes in credit supply linked to banking market structure. In the absence of frictions changes in local credit supply should not affect local firms, because there is a larger effect of changes in credit supply in counties dominated by small banks, it suggests that these lending markets are where frictions in the banking system are most problematic. Alternatively, in other lending markets, with a greater presence of large banks, there is an economically negligible effect on local firms, which is often not statistically significant. This indicates that the impact of some economically important frictions in the banking system has been reduced in these areas.

In order to address concerns regarding anticipation and spurious correlations, I graph coefficients as in Figure 3, but further subdivide high external finance and low external finance industries by bank size characteristics to form four separate subgroups in Figure 4. As can be seen, all subgroups trend similarly until time 0, when the subgroup that comprises high external finance requirement industries in high small bank market share counties trends higher.

To formally test the difference in coefficients across specifications in Table 6 and Figure 4, I estimate a regression form of difference-in-difference-in-differences, with the results shown in Table 7. This is done by adding additional interactions with small bank market share variables. The coefficient of interest in these tests is the triple interaction term $Boom_{i,t} * High_j * Small\ Bank_{i,t}$. A positive coefficient on the triple interaction term indicates that industries with high external finance requirements benefit more relative to industries low external finance requirements when there is a boom in an area with high small bank market share compared to other lending markets. Specifically, the interpretation of (1) in Table 7 is that high external finance requirement establishments increase by 6.2% relative to establishments in industries with low requirements for external finance in boom counties dominated by small banks relative to the difference between these industry groups in other boom counties.[14] Across all specifications the coefficient on $Boom_{i,t} * High_j * Small\ Bank_{i,t}$ is positive and statistically significant, providing evidence suggesting that higher small bank market share counties were more affected by economically important frictions in the banking system which may have disrupted the flow of capital. Specifically, if there were no frictions in the banking system to impede the flow of capital, additional deposits from the boom should not disproportionately affect high external finance requirement industries in high small bank market share counties.[15]

The results in Table 7 also address concerns regarding alternative explanations from the prior difference-in-differences tests conducted. An important concern is whether industries with high external finance requirements disproportionately benefit from a boom for a reason other than the credit supply component of a boom. For example, it could be the case that high external finance requirement industries benefit more in general when there is an economic boom (high asset beta). However, this explanation would not account for the differential impact experienced in high small bank market share counties relative to other lending markets. An additional concern may be that there could be more demand for goods and services for industries in the high external finance dependence industry group. However, in order for this explanation to be consistent with the results in Table 7, there would also

[14] Appendix B documents that similar and statistically significant results are obtained when different bank size and holding company definitions are used. Appendix C documents that similar and statistically significant results are obtained when holding the banking structure constant as of the year prior to the shale discovery.

[15] Appendix D documents that the largest increase in establishments is among establishments with fewer than 10 people, while establishment counts with 10 people or more are unaffected.

need to be a rationale for why this demand differential is relatively higher in counties with high small bank market share.

5.4 Validity of Experimental Design

5.4.1 Sensitivity of Results to Industry Classifications

A potential concern with my empirical design is whether local economic outcomes for industries with higher requirements for external finance improve relative to outcomes for industries with low requirements for external finance for some reason other than improved local credit supply. The difference-in-difference-in-differences tests help rule out several alternative explanations, however, an additional test of this assumption is included in Table 8. Specifically, for each industry group I calculate a measure of exposure to underlying economic fluctuations, asset beta, using two different asset beta methodologies.

$$\beta_{Asset1} = \frac{\beta_{Equity}}{1 + (1 - Tax\ Rate) * \frac{Debt}{Equity}}$$

$$\beta_{Asset2} = \frac{\beta_{Equity}}{1 + \frac{Debt}{Equity}}$$

The asset betas used are industry median asset betas. If it is the case that the asset betas for each industry group are different it could be cause for concern, as this would suggest that one industry group would be more sensitive to overall fluctuations in an economy. The results in Panel A of Table 8 provide evidence that the high external finance requirement industry group does have a higher asset beta. However, when the two highest asset beta industry groups are dropped from the regressions causing both industry groups to have similar asset betas, as in Panel B of Table 8, the interaction and triple interaction coefficients from the difference-in-differences regression and difference-in-difference-in-differences regression are still positive and statistically significant. This suggests that the difference in underlying asset betas between the groups is not driving my main results. Additionally Table 8 provides evidence that the regression results presented in Table 5 and Table 7 are not being driven by any single industry group in the study.

5.4.2 Non-Shale Growth Shock

Banking market structure is not randomly assigned, therefore, one concern may be that there are omitted factors which affect both a county's banking market structure as well as how certain industries (e.g. those with high external finance requirements) are affected by growth shocks. To attempt to assess whether such omitted factors may be affecting my estimates I conduct a test to assess whether non-shale growth shocks affect one industry group compared to another or one industry group relatively more in counties dominated by small banks. Specifically, in Table 9 I use data from the states immediately adjacent to the seven shale states to test whether non-shale growth shocks or "booms" affect the number of establishments in industries with high external finance requirements differently or the number of establishments in high external finance requirement industries in counties dominated by small banks differently. $Growth\ Shock_{i,t}$ dummy variables are inserted after high growth county-years so that the number of growth shock county years is approximately the same proportion as the number of shale boom county years obtained in the main sample (5% of all county-years). I obtain growth shock years by identifying years which experience a large increase in the number of business establishments, on average these growth shocks result in a 17.6% increase in establishments across all industries, a figure significantly higher than shale booms. The key coefficient of interest to test whether industries with high external finance requirements are affected differentially by these growth shocks is on the interaction term $Growth\ Shock_{i,t} * High_j$, this coefficient is not statistically significant. Additionally, the triple interaction term $Growth\ Shock_{i,t} * High_j * Small\ Bank_{i,t}$ is neither positive nor statistically significant. These results indicate that industries with high external finance requirements and industries with high external finance requirements in counties dominated by small banks are not differentially affected by general economic growth.

The primary difference between the growth shocks identified in Table 9, and the shale growth shocks used in this study is the relative importance of the credit supply component of the growth shock. Specifically, in a shale boom, overall establishments increase by 2.2% with significant variation linked to external finance requirements (documented in Table 5 and Table 7), bank deposits increase by 9.3%, more than four times the overall establishment increase. Alternatively, in the non-shale growth shocks establishments increase overall by 17.6%, while deposits increase by slightly less than half this amount, a deposit change of less than half the establishment increase compared to the more than four times relative increase in shale booms. These results suggest that the credit component of shale booms make shale growth shocks unique from general localized growth shocks.

5.4.3 Pre-existing Trends Placebo Test

An identifying assumption of a natural experiment is whether treatment and control groups would have behaved similarly in the absence of treatment. One way to provide evidence in support of this assumption is to test whether there are differential trends prior to treatment. To directly test whether any of the local economic outcome changes begin prior to a boom, I include dummy variables for the two years prior to the first shale development. These enter the regressions in the form of the $False\ Boom_{i,t}$ variable. As can be seen in the results in Table 10, neither the $False\ Boom_{i,t}$ variable, nor any of the interaction variables are statistically significant. This result provides direct evidence that the changes in economic outcome variables documented in this paper do not occur prior to the onset of shale development activity, and that there are no statistically significant pre-existing trends. Furthermore, because shale discoveries occur in different years in different counties (not just a single event in all counties at the same time), alternative interpretations of results would need to address changes in economic outcomes that happen to coincide with boom events in different locations at different points in time.

5.4.4 Are Demand Shocks from Shale Booms Correlated with Bank Size?

A potential concern for the validity of my empirical design is whether real shocks associated with a shale boom are larger in counties dominated by small banks relative to other counties. If this is the case, my interpretation of my empirical tests may be problematic. To provide evidence to alleviate this concern, I use retail sales data from the Economic Census conducted by the U.S. Census Bureau every 5 years. For this test, I use data on retail sales to proxy for demand in an area. The specific comparison I make is based on the 2002 and 2007 Economic Census data. Using this data I can test whether retail sales increase more in counties dominated by small banks after a boom relative to other counties after a boom. The key coefficient of interest in this test, is the interaction term $Boom_{i,t} * SmallBank_{i,t}$. If this coefficient is greater than 0, it would suggest that retail sales increase more in a county with a particular type of bank structure, and therefore indicate that demand shocks may be different across different counties. As can be seen in the specifications in Table 11, the coefficients on the interaction term $Boom_{i,t} * SmallBank_{i,t}$ are not statistically different from 0, suggesting that demand shocks are not correlated with bank size.

6 Conclusions

The United States has one of the most developed banking systems in the world. Prior research has demonstrated that deregulation, the adoption of lending technology and securitization, have led to improved economic outcomes. However, this paper provides new evidence that, after these improvements, there is significant cross sectional variation in the effect of information and agency frictions in the banking system. To identify this variation I use oil and gas shale discoveries to obtain exogenous variation in local credit supply to document where and when changes in local credit supply have the largest effect on local firms. If capital were able to flow, absent frictions, to fund positive net present value projects, changes in local credit supply would not affect local firms. Given that changes in local credit supply do affect local firms, it suggests that economically important frictions adversely affect the flow of capital in the banking system.

I find that cross sectional variation in the effect of changes in credit supply is strongly linked to local bank size. Areas dominated by small banks experience the biggest benefit, in the form of more business establishments in industries with greater external financing requirements, indicating that these lending markets suffer the most from information and agency frictions in the banking system. However, this paper also highlights an important bright side, as other lending markets with a greater presence of large banks do not experience changes in economic activity linked to changes in credit supply. This indicates that many of the advances in financial innovation, such as securitization and credit score models, may have served to mitigate economically important frictions in lending in these markets.

The evidence presented in this paper suggests that information and agency frictions in lending affect economic outcomes along two dimensions. In particular, the greater importance of local credit supply in areas dominated by small banks suggests that the combination of small banks facing frictions in obtaining external capital and borrowers in areas dominated by small banks facing frictions in obtaining loans has the biggest overall adverse impact on economic outcomes. These results would suggest that additional tools or innovations which could mitigate information or agency frictions for small banks in obtaining funding, may improve outcomes in areas dominated by small banks.

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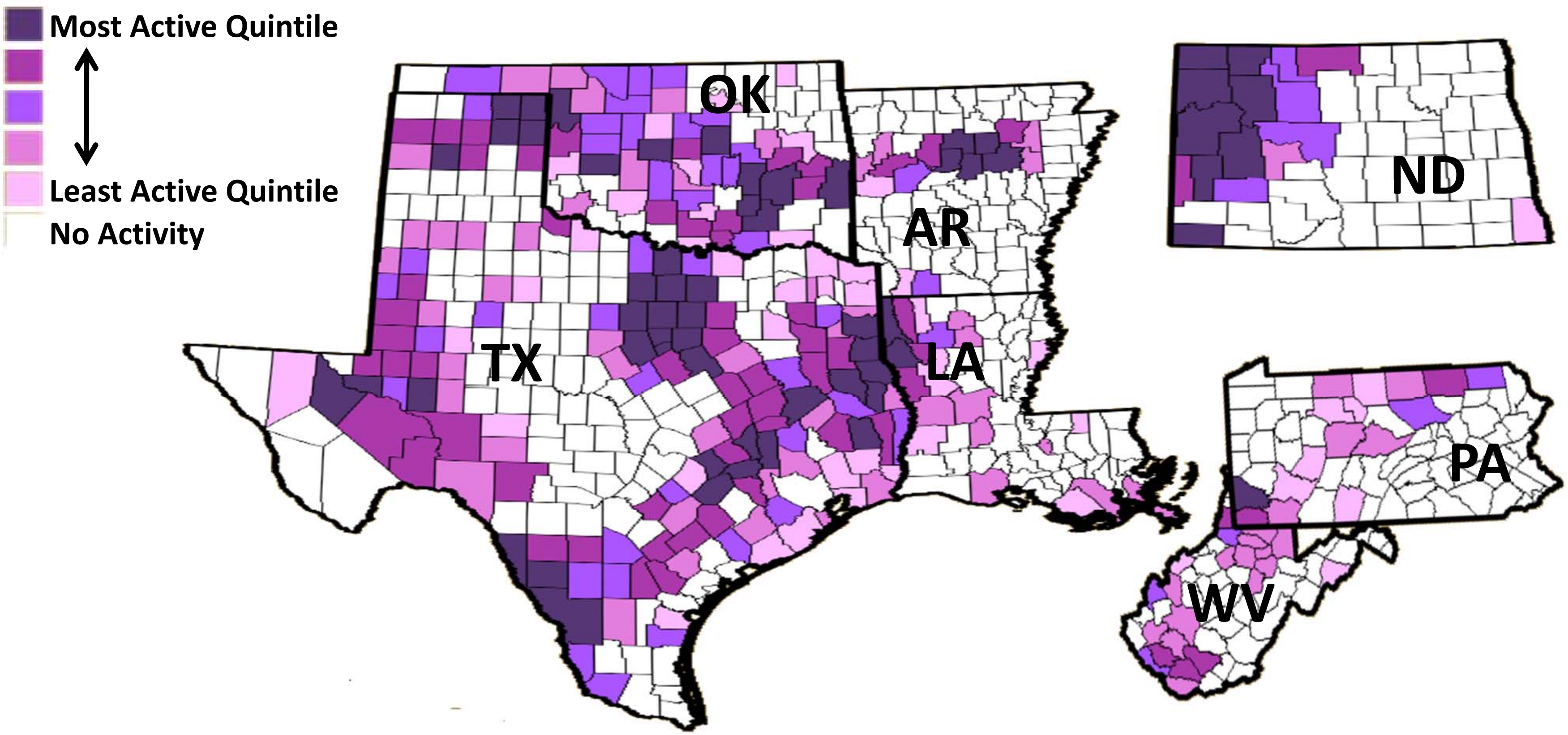

Figure 1: Location and Intensity of Shale Activity
The figure maps the counties of the 7 shale boom states included in this study: OK, TX, LA, WV, PA, ND and AR. White counties are counties with no shale development activity. The remaining counties are shaded based on intensity of activity related to the total number of shale wells drilled through 2009.

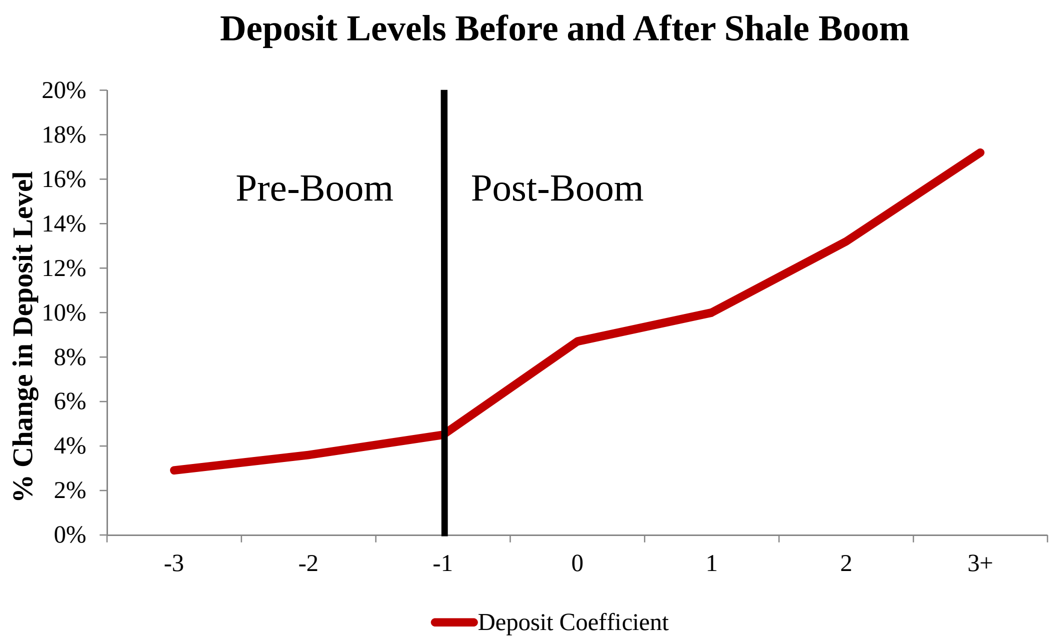

Figure 2: Deposit Levels Before and After Shale Boom

This figure plots the regression of dummy variables based on the year relative to a boom. The first year of a boom is year 0, and the definition of boom that is used is Boom Dummy (previously defined). For example, the first point is the plot of a dummy variable for time t-3 relative to the boom. Due to limited observations for times greater than t+3, all observations after time t+3 are grouped with the t+3 dummy (3+). The dependent variable is the logarithm of total deposits in the county, so the coefficients can be interpreted as the percentage change in the level of deposits at different points in time relative to the boom. Year fixed effects, and county fixed effects were included in the regression as well.

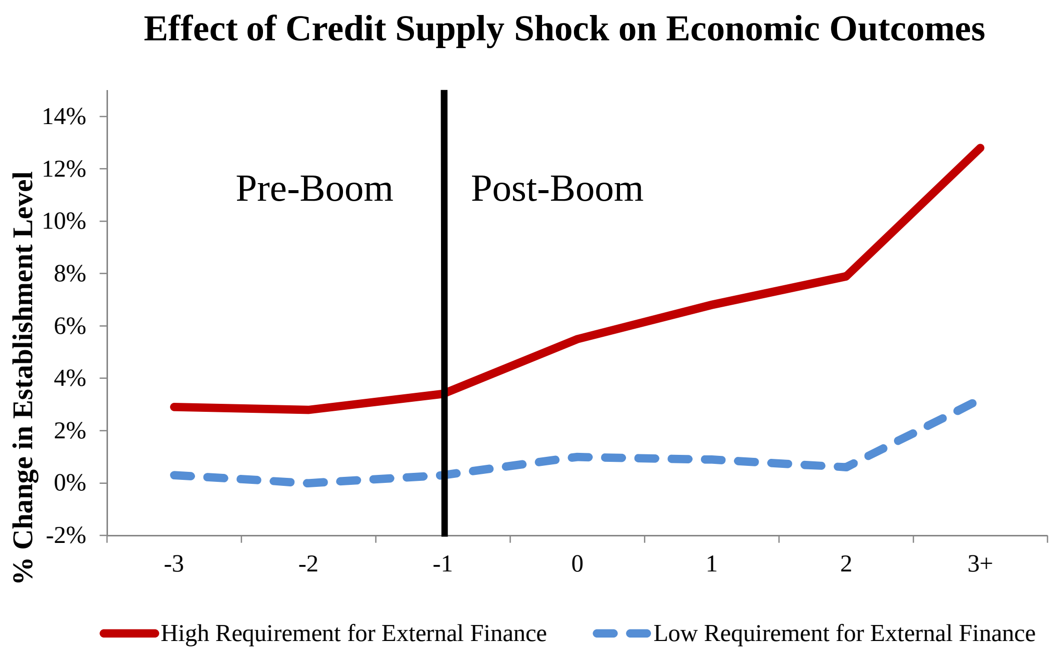

Figure 3: Establishment Levels Before and After Credit Supply Shock

This figure plots separately the regression coefficients of dummy variables of the year relative to a boom for industries with high requirements for external finance and low requirements for external finance. The first year of a boom is year 0, and the definition of boom that is used is Boom Dummy (previously defined). For example, the first point is the plot of a dummy variable for time t-3 relative to the boom. Due to limited observations for times greater than t+3, all observations after time t+3 are grouped with the t+3 dummy (3+). The dependent variable is logarithm of establishments in an industry in a county, so the coefficients can be interpreted as the percentage change in establishment levels at different points in time relative to the boom. Year fixed effects, and county fixed effects were included in the regression as well.

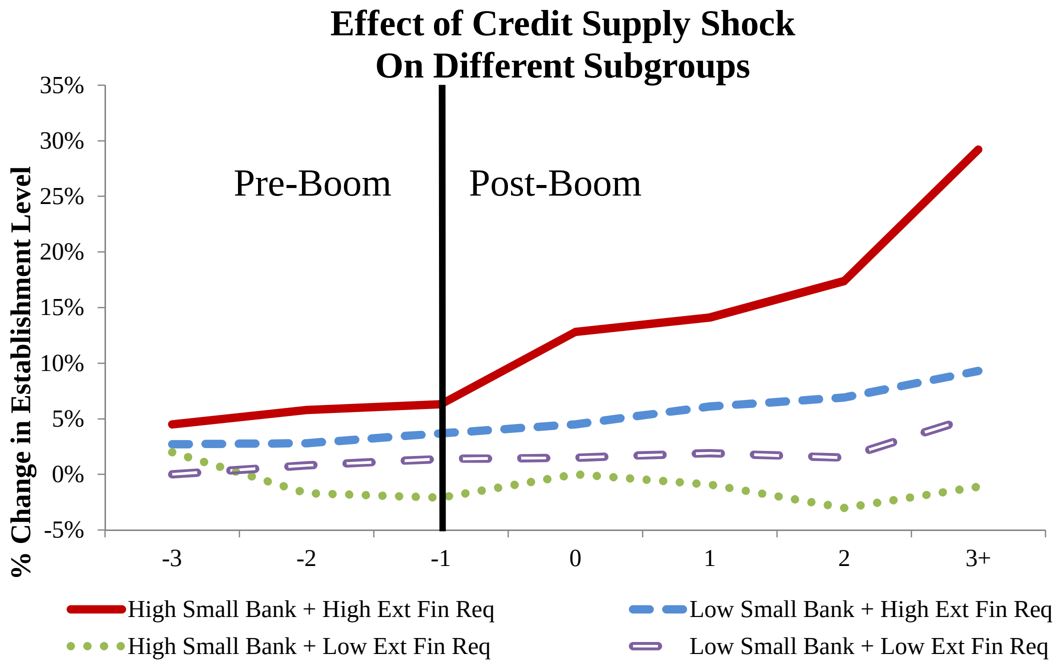

Figure 4: Effect of Credit Supply Shock on Counties with Different Bank Sizes

This figure plots separately the regression coefficients of dummy variables of the year relative to a boom for different subgroups. Specifically four different group designations are used based on whether an establishment has high or low requirements for external finance and whether it is in a county with high or low small bank market share. The first year of a boom is year 0, and the definition of boom that is used is Boom Dummy (previously defined). For example, the first point is the plot of a dummy variable for time t-3 relative to the boom. Due to limited observations for times greater than t+3, all observations after time t+3 are grouped with the t+3 dummy (3+). The dependent variable is logarithm of establishments in an industry in a county, so the coefficients can be interpreted as the percentage change in establishment levels at different points in time relative to the boom. Year fixed effects, and county fixed effects were included in the regression as well.

Table 1: Summary Statistics of States and Counties With Shale Booms

This table contains summary statistics for the well data used in this study. Development of shale and other unconventional formations is done using horizontal drilling, so I use horizontal well activity as the primary method of measuring when and where booms occur. The states in the sample are states situated in the primary shale development areas: Barnett (TX), Woodford (OK), Haynesville (LA + TX), Fayetteville (AR), Marcellus (PA + WV), Eagle Ford (TX), Bakken (ND). Well data was obtained from Smith International Inc.

Panel A: States, Counties, Shale Well Activity

Number of States	7
Number of Counties	639
Number of Boom Counties	104
Total Number of Shale Wells	16,731
Time Period	2000 - 2009

Panel B: Shale Discoveries ("Booms")

	County	Boom Year		County	Boom Year
1	Bowman County, North Dakota	2003	53	Bosque County , Texas	2007
2	Brazos County, Texas	2003	54	Ector County , Texas	2007
3	Moore County, Texas	2003	55	Erath County , Texas	2007
4	Potter County, Texas	2003	56	Hill County , Texas	2007
5	Upton County, Texas	2003	57	Jack County , Texas	2007
6	Washington County, Texas	2003	58	Jasper County , Texas	2007
7	Haskell County, Oklahoma	2004	59	Madison County , Texas	2007
8	Pittsburg County, Oklahoma	2004	60	Midland County , Texas	2007
9	Denton County, Texas	2004	61	Panola County , Texas	2007
10	Fayette County, Texas	2004	62	Somervell County , Texas	2007
11	Grimes County, Texas	2004	63	Webb County , Texas	2007
12	Johnson County, Texas	2004	64	Zavala County , Texas	2007
13	Lipscomb County, Texas	2004	65	Cleburne County , Arkansas	2008
14	Maverick County, Texas	2004	66	Atoka County , Oklahoma	2008
15	Shelby County, Texas	2004	67	Latimer County , Oklahoma	2008
16	Terrell County, Texas	2004	68	Lincoln County , Oklahoma	2008
17	Wise County, Texas	2004	69	Roger Mills County , Oklahoma	2008
18	De Soto County, Louisiana	2005	70	Washita County , Oklahoma	2008
19	Billings County, North Dakota	2005	71	Andrews County , Texas	2008
20	McKenzie County, North Dakota	2005	72	De Witt County , Texas	2008
21	Williams County, North Dakota	2005	73	Edwards County , Texas	2008
22	Le Flore County, Oklahoma	2005	74	Ellis County , Texas	2008
23	Gaines County, Texas	2005	75	Freestone County , Texas	2008
24	Hardeman County, Texas	2005	76	Harrison County , Texas	2008
25	Lee County, Texas	2005	77	Hemphill County , Texas	2008
26	Nacogdoches County, Texas	2005	78	Hutchinson County , Texas	2008
27	Parker County, Texas	2005	79	Karnes County , Texas	2008
28	Pecos County, Texas	2005	80	Lavaca County , Texas	2008
29	Reeves County, Texas	2005	81	Live Oak County , Texas	2008
30	Tarrant County, Texas	2005	82	Montague County , Texas	2008
31	Tyler County, Texas	2005	83	Palo Pinto County , Texas	2008
32	Divide County, North Dakota	2006	84	Polk County , Texas	2008
33	Golden Valley County, North Dakota	2006	85	Robertson County , Texas	2008
34	Coal County, Oklahoma	2006	86	Winkler County , Texas	2008
35	Bee County, Texas	2006	87	Logan County , Arkansas	2009
36	Burleson County, Texas	2006	88	Bossier County , Louisiana	2009
37	Dimmit County, Texas	2006	89	Caddo County , Louisiana	2009
38	Hood County, Texas	2006	90	Red River County , Louisiana	2009
39	Houston County, Texas	2006	91	Sabine County , Louisiana	2009
40	Ochiltree County, Texas	2006	92	Bottineau County , North Dakota	2009
41	Roberts County, Texas	2006	93	Canadian County , Oklahoma	2009
42	Ward County, Texas	2006	94	Carter County , Oklahoma	2009
43	Conway County, Arkansas	2007	95	Johnston County , Oklahoma	2009
44	Faulkner County, Arkansas	2007	96	Marshall County , Oklahoma	2009
45	Van Buren County, Arkansas	2007	97	Greene County , Pennsylvania	2009
46	White County, Arkansas	2007	98	Washington County , Pennsylvania	2009
47	Burke County, North Dakota	2007	99	Cherokee County , Texas	2009
48	Dunn County, North Dakota	2007	100	Dallas County , Texas	2009
49	Mountrail County, North Dakota	2007	101	Leon County , Texas	2009
50	Ellis County, Oklahoma	2007	102	San Augustine County , Texas	2009
51	Hughes County, Oklahoma	2007	103	Wheeler County , Texas	2009
52	Oklahoma County, Oklahoma	2007	104	Wood County , Texas	2009

Table 2: Panel Regression Summary Statistics

This table contains summary statistics for the data used in the panel regressions. The unit of observation for economic outcome variables is business establishment counts in a panel data set at the county-year-industry (external finance industry group) level, while the unit of observation for bank deposits is at the county-year level. Data on establishments is from the County Business Patterns survey. Economic outcome variables are summed across all industries into two groups based on an industry's requirements for external finance. Hence for each county-year there are two industry groups, one with high requirements for external finance and one with low requirements for external finance. Data on annual population levels are from the Census Bureau. Small Banks are categorized as banks with less than $500 million in assets, adjusted for inflation (year 2003 dollars). Bank data was compiled from the FDIC Summary of Deposit reports. Shale well information is based on well data obtained from Smith International Inc.

	Obs	Mean	Std Dev
Deposits			
Log Deposits	6,382	12.60	1.41
Deposits ($ in thousands)	6,382	1,195,253	5,228,131
Economic Outcomes			
Log Establishments	12,764	5.24	1.44
Establishments	12,764	680	2,193
Establishments per Capita (per 10,000 people)	12,764	84.81	34.14
Control/Explanatory Variables			
Log Total Shale Wells	12,764	0.45	1.07
Small Bank Branch Market Share	12,764	0.63	0.30

Table 3: External Finance Requirements of Industries

This table reports the industry groups used in this study. The industry groups are based on the two digit North American Industry Classification System used in the reporting of the County Business Patterns survey, which is reported annually by the Census Bureau. For each industry a measure of dependence on external finance is calculated, based on the method used by Rajan and Zingales (1998). The external finance requirement measure reported for each industry is the industry median requirement for external finance. The data used to calculate the external finance dependence measure is from Compustat for the period from 1999 to 2008 (the fiscal years that are closest to the March data collection of the County Business Patterns survey from 2000 to 2009). The economic outcome measures used are aggregated into two separate industry groups in each county, one with above median dependence on external finance (External Dependence Flag = 1), and one with below median dependence on external finance (External Dependence Flag = 0).

Two Digit NAICS	Two Digit NAICS Name	External Requirement Measure	External Dependence Flag
81	Other Services (except Public Administration)	-0.505	0
42	Wholesale Trade	-0.360	0
62	Health Care and Social Assistance	-0.175	0
44	Retail Trade	-0.127	0
11	Agriculture, Forestry, Fishing and Hunting	-0.079	0
61	Educational Services	-0.012	0
22	Utilities	-0.004	0
48	Transportation and Warehousing	0.071	1
56	Administrative and Support and Waste Management and Remediation Services	0.105	1
72	Accommodation and Food Services	0.183	1
71	Arts, Entertainment, and Recreation	0.418	1
31	Manufacturing	0.475	1
54	Professional, Scientific, and Technical Services	1.023	1
51	Information	1.097	1

Table 4: Effect of Shale Booms on Bank Deposits

This table reports the results of regressions which measure the effect of different boom variables on deposits. The dependent variables in these regressions is the log of total deposits in county i in year t and the log of total deposits per capita in county i year t. The explanatory variables are different shale boom variables, which have previously been defined. County and year fixed effects are included to control for time effects and time invariant county effects. Panel A documents the effect of a shale boom on county bank deposits, while Panel B tests whether there is a differential effect on bank deposits based on local bank size. The Small Bank Dummy variable used in Panel B is equal to 1 if a county has above median small bank branch market share in a given year, and 0 otherwise. Panel B includes the interacted fixed effects of Small $\text{Bank}_{i,t}$ * Year FE_t to control for differing trends in deposits across counties with different banking market structures. The definition of small bank in these regressions is any bank with less than \$500 million in assets adjusted for inflation. Standard errors are clustered by county, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

$$Deposits_{i,t} = \alpha + \beta_1 Boom_{i,t} + Year\ FE_t + County\ FE_i + \varepsilon_{i,t}$$

Panel A: Effect of Shale Booms on Bank Deposits

	Dependent Variable = Log Deposits		Dependent Variable = Log Deposits per Capita	
	Boom = Dummy	Boom = Log Total Shale Wells	Boom = Dummy	Boom = Log Total Shale Wells
	(1)	(2)	(3)	(4)
$\text{Boom}_{i,t}$	0.093***	0.026***	0.073***	0.018***
	(4.49)	(4.42)	(3.70)	(3.24)
Year FE_t	Yes	Yes	Yes	Yes
County FE_i	Yes	Yes	Yes	Yes
R^2 - Within	0.631	0.634	0.604	0.604
N	6,382	6,382	6,382	6,382

$$Deposits_{i,t} = \alpha + \beta_1 Boom_{i,t} + \beta_2 Small\ Bank_{i,t} + \beta_3 Boom_{i,t} * Small\ Bank_{i,t} + Small\ Bank_{i,t} * Year\ FE_t + County\ FE_i + \varepsilon_{i,t}$$

Panel B: Effect of Shale Boom on Bank Deposits: Counties With Different Bank Sizes

	Dependent Variable = Log Deposits		Dependent Variable = Log Deposits per Capita	
	Small Bank = Dummy		Small Bank = Dummy	
	Boom = Dummy	Boom = Log Total Shale Wells	Boom = Dummy	Boom = Log Total Shale Wells
	(1)	(2)	(3)	(4)
$\text{Boom}_{i,t}$	0.127***	0.029***	0.097**	0.020**
	(3.16)	(2.76)	(2.53)	(2.01)
Small $\text{Bank}_{i,t}$	Absorbed by Small $\text{Bank}_{i,t}$ x Year FE_t			
$\text{Boom}_{i,t}$ * Small $\text{Bank}_{i,t}$	-0.047	-0.002	-0.037	-0.002
	(-1.13)	(-0.17)	(-0.94)	(-0.20)
Small $\text{Bank}_{i,t}$ x Year FE_t	Yes	Yes	Yes	Yes
County FE_i	Yes	Yes	Yes	Yes
R^2 - Within	0.641	0.643	0.608	0.607
N	6,382	6,382	6,382	6,382

Table 5: Effect of Credit Supply Shock on Firms: Difference-in-Differences
(Boom vs. Non-Boom, High Ext Finance Requirements vs. Low Ext Finance Requirements)
This table reports the results of regressions measuring the effect of a credit supply shock on local firms by comparing the change in establishments between two industry groups, one which has high requirements for external finance (Ind = High) and one which has low requirements for external finance (Ind = Low). The dependent variables in these regressions are log establishments and establishments per capita (per 10,000 people). The regression estimates are a regression form of difference-in-differences and test change in establishments before the boom versus after the boom across industries groups with different external finance requirements. County-industry and industry-year (industry trends) fixed effects are included, as well as county-year fixed effects. Note, reported R squared is close to one, due to the inclusion of these high dimensional fixed effects. Standard errors are clustered by county, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

$$Establishments_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + \beta_2 High_j + \beta_3 Boom_{i,t} * High_j + IndustryYearFE_{j,t} + CountyIndustry\ FE_{i,j} + CountyYearFE_{i,t} + \varepsilon_{i,j,t}$$

	Dependent Variable = Log Establishments		Dependent Variable = Establishments per Capita	
	Boom = Dummy	Boom = Log Total Shale Wells	Boom = Dummy	Boom = Log Total Shale Wells
	(1)	(2)	(3)	(4)
$Boom_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
$High_j$	Absorbed by County x Industry $FE_{i,j}$			
$Boom_{i,t}$ * $High_j$	0.046***	0.012***	3.629***	0.974***
	(2.67)	(2.61)	(2.71)	(2.78)
Industry x Year $FE_{j,t}$	Yes	Yes	Yes	Yes
County x Industry $FE_{i,j}$	Yes	Yes	Yes	Yes
County x Year $FE_{i,t}$	Yes	Yes	Yes	Yes
R^2 - Within	0.008	0.008	0.008	0.009
N	12,764	12,764	12,764	12,764

Table 6: Effect of Credit Supply Shock on Firms: Subdivided by Small Bank Market Share
(Boom vs. Non-Boom, High External Finance Requirements vs. Low External Finance Requirements)

This table reports a regression form of difference-in-differences for two different county groups, one county group which has high small bank market share (Bank = High Small Bank Mkt Share), and one county group with low small bank market share (Bank = Low Small Bank Mkt Share). The definition of small bank in these regressions is any bank with less than $500 million in assets adjusted for inflation. For this regression high small bank market share counties are defined to be counties with above median small bank branch market share. The dependent variables in these regressions are log of establishments and establishments per capita (per 10,000 people). The explanatory variables are different shale boom variables, which have previously been defined. Additionally, an interaction between boom variables and the "High" external finance dependence dummy is included, this is the difference-in-differences coefficient of interest (β_3). County-industry and industry-year (industry trends) fixed effects are included, as well as county-year fixed effects. Note, reported R squared is close to one, due to the inclusion of these high dimensional fixed effects. Standard errors are clustered by county, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

$$Establishments_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + \beta_2 High_j + \beta_3 Boom_{i,t} * High_j + IndustryYear\ FE_{j,t} + CountyIndustry\ FE_{i,j} + CountyYear\ FE_{i,t} + \varepsilon_{i,j,t}$$

	Dependent Variable = Log Establishments				Dependent Variable = Establishments per Capita			
	Boom = Dummy		Boom = Log Total Shale Wells		Boom = Dummy		Boom = Log Total Shale Wells	
	High Small Bank Market Share	Low Small Bank Market Share	High Small Bank Market Share	Low Small Bank Market Share	High Small Bank Market Share	Low Small Bank Market Share	High Small Bank Market Share	Low Small Bank Market Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Boom_{i,t}$	Absorbed by County x Year $FE_{i,t}$							
$High_j$	Absorbed by County x Industry $FE_{i,j}$							
$Boom_{i,t}$ * $High_j$	0.071***	0.012	0.019***	0.004*	4.905***	1.443	1.453***	0.329
	(3.10)	(1.09)	(2.86)	(1.73)	(3.03)	(1.35)	(3.16)	(1.46)
Industry x Year $FE_{j,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Industry $FE_{i,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year $FE_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 - Within	0.014	0.001	0.013	0.003	0.011	0.003	0.013	0.002
N	6,502	6,262	6,502	6,262	6,502	6,262	6,502	6,262

Table 7: Effect of Bank Size and Credit Supply on Firms: Differences-in-Differences-in-Differences Regression
(Boom vs. Non-Boom, High Ext Finance Requirements vs. Low Ext Finance Requirements, High Small Bank Market Share vs. Low Small Bank Market Share)

This table reports results for a regression form of difference-in-difference-in-differences, where the coefficient of interest is the triple interaction term. The dependent variables in these regressions are log establishments or establishments per capita (per 10,000 people) in county *i* , year *t* , industry group *j* . The explanatory variables are different boom variables, which have previously been defined. The definition of small bank in these regressions is any bank with less than $500 million in assets adjusted for inflation. These specifications provide results for two different measures of Small $Bank_{i,t}$. One measure is a dummy variable, set to 1 if a county has above median small bank branch market share in any given year and 0 otherwise (Small Bank = Dummy), while the other measure is the ratio of branches which belong to small banks relative to the total number of bank branches in a county (Small Bank = Ratio). Additionally, a set of fully saturated interactions between Boom variables, Small Bank variables, and the High external finance dependence dummy are included. The key coefficient of interest for the difference-in-difference-in-differences regression is the triple interaction term β_7. County-industry and industry-year (industry trends) fixed effects are included, as well as county-year fixed effects. Note, reported R squared is close to one, due to the inclusion of these high dimensional fixed effects. Standard errors are clustered by county, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

$$Establishments_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + \beta_2 High_j + \beta_3 Small\ Bank_{i,t} + \beta_4 Boom_{i,t} * High_j + \beta_5 Boom_{i,t} * Small\ Bank_{i,t}$$
$$+ \beta_6 High_j * Small\ Bank_{i,t} + \beta_7 Boom_{i,t} * Small\ Bank_{i,t} * High_j + IndustryYear\ FE_{j,t} + CountyIndustry\ FE_{i,j} + CountyYear\ FE_{i,t} + \varepsilon_{i,j,t}$$

	Dependent = Log Establishments				Dependent = Establishments per Capita			
	Boom = Dummy		Boom = Log Shale Wells		Boom = Dummy		Boom = Log Shale Wells	
	Bank = Dummy	Bank = Ratio	Bank = Dummy	Bank = Ratio	Bank = Dummy	Bank = Ratio	Bank = Dummy	Bank = Ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Boom_{i,t}$	Absorbed by County x Year $FE_{i,t}$							
$High_j$	Absorbed by County x Industry $FE_{i,j}$							
Small $Bank_{i,t}$	Absorbed by County x Year $FE_{i,t}$							
$Boom_{i,t}$ * $High_j$	0.008	-0.065*	0.003	-0.015*	0.742	-3.079	0.207	-0.937
	(0.49)	(-1.78)	(0.84)	(-1.80)	(0.48)	(-1.05)	(0.59)	(-1.49)
$Boom_{i,t}$ * Small $Bank_{i,t}$	Absorbed by County x Year $FE_{i,t}$							
Small $Bank_{i,t}$ * $High_j$	-0.010	0.023	-0.013	0.011	-0.319	3.803	-0.656	2.767
	(-1.20)	(0.91)	(-1.49)	(0.44)	(-0.37)	(1.32)	(-0.76)	(0.97)
$Boom_{i,t}$ * Small $Bank_{i,t}$ * $High_j$	0.062**	0.172**	0.015**	0.043***	4.715**	10.378**	1.371***	3.127***
	(2.14)	(2.54)	(2.24)	(2.66)	(2.09)	(2.11)	(2.70)	(2.81)
Industry x Year $FE_{j,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Industry $FE_{i,j}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year $FE_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 - Within	0.013	0.020	0.013	0.021	0.011	0.017	0.015	0.022
N	12,764	12,764	12,764	12,764	12,764	12,764	12,764	12,764

Table 8: Sensitivity of Results to Different Industries

Panel A: This panel reports regression results of the key interaction coefficients of interest when excluding specific industries from the regression results originally reported in Table 5 (column (2) below) and Table 7 (column (3) below). The definition of Boom variable used in these regressions is log total shale wells, and the definition of Small Bank Share is a dummy variable for counties with above median small bank branch market share. Additionally this table reports the asset beta for each industry, using two different methodologies.

Panel B: This panel reports regression results of the key interaction coefficients of interest when excluding the two highest asset beta industries from the regression results originally reported in Table 5 (column (2) below) and Table 7 (column (3) below). The definition of Boom variable used in these regressions is log total shale wells, and the definition of Small Bank Share is a dummy variable for counties with above median small bank branch market share. Columns (6) and (7) report the average asset beta for each industry group when the two highest asset beta industry groups are excluded.

Panel A

Industries		Excluding Industry			Asset Beta By Industry	
(1) Two Digit NAICS	(2) Two Digit NAICS Name	(3) $Boom_{i,t}$ * $High_j$	(4) $Boom_{i,t}$ * Small $Bank_{i,t}$ * $High_j$	(5) Ext Finance Dependence Flag	(6) β_{Asset1}	(7) β_{Asset2}
62	Health Care and Social Assistance	0.011***	0.012*	0	0.64	0.61
42	Wholesale Trade	0.012***	0.015**	0	0.79	0.77
11	Agriculture, Forestry, Fishing and Hunting	0.011**	0.015**	0	0.40	0.42
61	Educational Services	0.012***	0.015**	0	0.86	0.83
81	Other Services (except Public Administration)	0.011**	0.016**	0	0.51	0.49
44	Retail Trade	0.013***	0.019***	0	0.82	0.77
22	Utilities	0.010**	0.014**	0	0.21	0.21
56	Administrative and Support and Waste Management and Remediation Services	0.011***	0.013**	1	0.82	0.80
48	Transportation and Warehousing	0.009**	0.011*	1	0.60	0.58
31	Manufacturing	0.012***	0.012*	1	0.51	0.50
72	Accommodation and Food Services	0.013**	0.018**	1	0.61	0.59
71	Arts, Entertainment, and Recreation	0.013***	0.015**	1	0.69	0.64
54	Professional, Scientific, and Technical Services	0.012***	0.019***	1	1.18	1.19
51	Information	0.012**	0.016**	1	1.39	1.38
	Average for Low Dependence on External Finance				0.60	0.59
	Average for High Dependence on External Finance				0.83	0.81

Panel B

Industries		Excluding Industry			Asset Beta By Industry	
(1) Two Digit NAICS	(2) Two Digit NAICS Name	(3) $Boom_{i,t}$ * $High_j$	(4) $Boom_{i,t}$ * Small $Bank_{i,t}$ * $High_j$	(5) Ext Finance Dependence Flag	(6) β_{Asset1}	(7) β_{Asset2}
51-54	Two Highest Beta Industries (Codes 51 and 54)	0.012**	0.020***	1		
	Average Asset Beta of Low Dependence (Exclude Codes 51 and 54)				0.60	0.59
	Average Asset Beta of High Dependence (Exclude Codes 51 and 54)				0.65	0.62

Table 9: Effect of Non-Shale Growth Shocks on Firms

This table reports estimates of regressions similar to those presented in Tables 5 and 7, except the shocks used are non-shale growth shocks in states adjacent to the seven shale states in this study. Specifically, dummy "Growth Shock" variables are inserted after high growth county-years such that the number of Growth Shock county years is approximately the same proportion of Shale Boom county years obtained in the main sample (roughly 5% of all county-years). The objective of this specification is to test whether general growth shocks differentially affect a particular industry group or a particular set of industries in counties dominated by small banks. The dependent variables in these regressions are log establishments or establishments per capita (per 10,000 people) in county i, year t, industry group j. Note, reported R squared is close to one, due to the inclusion of multiple high dimensional fixed effects. Standard errors are clustered by county, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Dependent Variable = Log Establishments		Dependent Variable = Establishments per Capita	
	Growth Shock = Dummy		Growth Shock = Dummy	
	Small Bank Share = Dummy		Small Bank Share = Dummy	
	(1)	(2)	(3)	(4)
Growth Shock$_{i,t}$	Absorbed by County x Year FE$_{i,t}$			
High$_j$	Absorbed by County x Industry FE$_{i,j}$			
Small Bank$_{i,t}$	Absorbed by County x Year FE$_{i,t}$			
Growth Shock$_{i,t}$ * High$_j$	0.002	0.011	-3.591	-3.480
	(0.07)	(0.52)	(-1.54)	(-1.29)
Growth Shock$_{i,t}$ * Small Bank$_{i,t}$	Absorbed by County x Year FE$_{i,t}$			
Small Bank$_{i,t}$ * High$_j$		-0.002		-0.468
		(-0.25)		(-0.59)
Growth Shock$_{i,t}$ * Small Bank$_{i,t}$ * High$_j$		-0.027		-0.338
		(-0.83)		(-0.10)
Industry x Year FE$_{j,t}$	Yes	Yes	Yes	Yes
County x Industry FE$_{i,j}$	Yes	Yes	Yes	Yes
County x Year FE$_{i,t}$	Yes	Yes	Yes	Yes
R^2 - Within	0.000	0.001	0.003	0.003
N	22,932	22,932	22,932	22,932

Table 10: Placebo Test of Pre-Boom Trends

This table reports results of falsification tests for the regressions in Tables 5 and 7. Specifically, dummy variables are inserted for the two years prior to the beginning of shale well activity. The dependent variables in these regressions are log establishments or establishments per capita (per 10,000 people) in county i, year t, industry group j. Note, reported R squared is close to one, due to the inclusion of multiple high dimensional fixed effects. Standard errors are clustered by county, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

$$(1)\ Establishments_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + \beta_{1F} False\ Boom_{i,t} + \beta_2 High_j + \beta_3 Boom_{i,t} * High_j + \beta_{3F} False\ Boom_{i,t} * High_j + IndustryYear\ FE_{j,t} + CountyIndustry\ FE_{i,j} + CountyYear\ FE_{i,t} + \varepsilon_{i,j,t}$$

$$(2)\ Establishments_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + \beta_{1F} False\ Boom_{i,t} + \beta_2 High_j + \beta_3 Small\ Bank_{i,t} + \beta_4 Boom_{i,t} * High_j + \beta_{4F} False\ Boom_{i,t} * High_j + \beta_5 Boom_{i,t} * Small\ Bank_{i,t} + \beta_{5F} False\ Boom_{i,t} * Small\ Bank_{i,t} + \beta_6 High_j * Small\ Bank_{i,t} + \beta_7 Boom_{i,t} * Small\ Bank_{i,t} * High_j + \beta_{7F} False\ Boom_{i,t} * Small\ Bank_{i,t} * High_j + IndustryYear\ FE_{j,t} + CountyIndustry\ FE_{i,j} + CountyYear\ FE_{i,t} + \varepsilon_{i,j,t}$$

	Dependent Variable = Log Establishments		Dependent Variable = Establishments per Capita	
	False Boom = Dummy, Boom = Log Total Shale Wells		False Boom = Dummy, Boom = Log Total Shale Wells	
	Small Bank = Dummy		Small Bank = Dummy	
	(1)	(2)	(3)	(4)
$Boom_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
False $Boom_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
$High_j$	Absorbed by County x Industry $FE_{i,j}$			
Small $Bank_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
$Boom_{i,t}$ * $High_j$	0.012**	0.004	1.046***	0.236
	(2.52)	(0.83)	(2.72)	(0.58)
False $Boom_{i,t}$ * $High_j$	0.002	0.001	0.289	0.000
	(0.35)	(0.15)	(0.64)	(0.00)
$Boom_{i,t}$ * Small $Bank_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
False $Boom_{i,t}$ * Small $Bank_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
Small Bank $Share_{i,t}$ * $High_j$		-0.013		-0.809
		(-1.60)		(-0.97)
$Boom_{i,t}$ * Small $Bank_{i,t}$ * $High_j$		0.016**		1.477**
		(2.19)		(2.54)
False $Boom_{i,t}$ * Small $Bank_{i,t}$ * $High_j$		0.003		0.624
		(0.28)		(0.58)
Industry x Year $FE_{j,t}$	Yes	Yes	Yes	Yes
County x Industry $FE_{i,j}$	Yes	Yes	Yes	Yes
County x Year $FE_{i,t}$	Yes	Yes	Yes	Yes
R^2 - Within	0.008	0.013	0.009	0.015
N	12,764	12,764	12,764	12,764

Table 11: Retail Sales Changes in Boom Counties with Different Local Bank Sizes

This table reports the results of regressions which estimate the effect of different boom variables on retail sales. The dependent variable in these regressions is the log of total retail sales by establishments in county i in year t. The regressions test whether there is a differential effect on retail sales based on local bank size. The Small Bank Dummy variable used is equal to 1 if a county has above median small bank branch market share in a given year, and 0 otherwise. The definition of small bank in these regressions is any bank with less than $500 million in assets adjusted for inflation. Retail sales data is from the U.S. Bureau of the Census Economic Census in 2002 and 2007 (conducted every 5 years). Standard errors are clustered by county, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

$$\textit{Log Retail Sales}_{i,t} = \alpha + \beta_1 \textit{Log Population}_{i,t} + \beta_2 \textit{Boom}_{i,t} + \beta_3 \textit{Small Bank}_{i,t}$$
$$+ \beta_4 \textit{Boom}_{i,t} * \textit{Small Bank}_{i,t} + \text{Year } \textit{FE}_t + \textit{County FE}_i + \varepsilon_{i,t}$$

Effect of Shale Boom on Retail Sales: Counties With Different Bank Sizes

	Small Bank = Dummy	
	Boom = Dummy	Boom = Log Total Shale Wells
	(1)	(2)
$Boom_{i,t}$	0.048*	0.016***
	(1.65)	(2.67)
Small $Bank_{i,t}$	0.021	0.015
	(0.90)	(0.57)
$Boom_{i,t}$ * Small $Bank_{i,t}$	-0.064	0.003
	(-0.76)	(0.16)
Log $Population_{i,t}$	0.669***	0.661***
	(8.34)	(8.22)
Year FE_t	Yes	Yes
County FE_i	Yes	Yes
R^2-Within	0.670	0.673
N	1,263	1,263

Appendix: For Online Publication

Appendix A: Regressions for Banks with All Branches in One County

This table reports the results of regressions which estimate the effect of different shale boom variables on bank outcomes for banks that have all of their branches in a single county. The unit of observation in this panel is county *i* , bank *j* , year *t* . Data on banks was compiled from Call Reports and Summary of Deposit reports. A bank is in the sample if all of its branches are in a single county in given year, treatment banks are those banks which are in shale boom county-years, while control banks are single county banks in non-shale boom county-years. C&I loans are the total amount of commercial and industrial loans a bank reports on its Call Report. Interest income is the total interest income a bank generates in a year, divided by its average total loans. Deposit Interest Rate is the interest paid on all deposits divided by the average amount of deposits a bank has in a given year. Both interest rate and deposit interest rate variables were winsorized at 1% and 99%. Year fixed effects and bank fixed effects are included. Standard errors are clustered by bank, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

$$Bank\ Outcome_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + Year\ FE_t + Bank\ FE_j + \varepsilon_{i,j,t}$$

Panel A

	Boom = Dummy				
	Outcome = Log Deposits	Outcome = Log C&I Loans	Outcome = Interest Rate	Outcome = Deposit Interest Rate	Outcome = Non-Performing Loan Ratio
	(1)	(2)	(3)	(4)	(5)
$Boom_{i,t}$	0.0960***	0.1072**	0.0004	0.0004	-0.0008
	(4.24)	(2.45)	(0.12)	(1.16)	(-0.91)
Year FE_t	Yes	Yes	Yes	Yes	Yes
Bank FE_j	Yes	Yes	Yes	Yes	Yes
R^2 - Within	0.374	0.102	0.399	0.871	0.024
N	8,176	8,176	8,176	8,176	8,176

Panel B

	Boom = Log Total Shale Wells				
	Outcome = Log Deposits	Outcome = Log C&I Loans	Outcome = Interest Rate	Outcome = Deposit Interest Rate	Outcome = Non-Performing Loan Ratio
	(1)	(2)	(3)	(4)	
$Boom_{i,t}$	0.0277***	0.0316***	-0.0007	0.0000	-0.0004**
	(4.37)	(2.69)	(-0.88)	(0.36)	(-2.03)
Year FE_t	Yes	Yes	Yes	Yes	Yes
Bank FE_j	Yes	Yes	Yes	Yes	Yes
R^2 - Within	0.376	0.103	0.399	0.871	0.025
N	8,176	8,176	8,176	8,176	8,176

Appendix B: Alternative Thresholds for Small Bank Size

(Boom vs. Non-Boom, High Ext Finance Requirements vs. Low Ext Finance Requirements High Small Bank Market Share vs. Low Small Bank Market Share)

This table reports results for a regression form of difference-in-difference-in-differences, where the coefficient of interest is the triple interaction term. The dependent variable in these regressions is log establishments in county *i* , year *t* , industry group *j* . This table reports specifications using different small bank definitions. The regressions in this table report results for small bank cutoffs at $200 million, $500 million, and $1 billion in assets adjusted for inflation. Additionally, the specifications report results for assets measured both at the bank level and at the bank holding company level. $Small\ Bank_{i,t}$ is a dummy variable, set to 1 if a county has above median small bank branch market share in any given year and 0 otherwise (Small Bank = Dummy). A set of fully saturated interactions between Boom variables, Small Bank variables, and the High external finance requirement dummy are included. The key coefficient of interest for the difference-in-difference-in-differences regression is the triple interaction term β_7. Note, reported R squared is close to one, due to the inclusion of multiple high dimensional fixed effects. Standard errors are clustered by county, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

$$Establishments_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + \beta_2 High_j + \beta_3 Small\ Bank_{i,t} + \beta_4 Boom_{i,t} * High_j + \beta_5 Boom_{i,t} * Small\ Bank_{i,t}$$

$$+ \beta_6 High_j * Small\ Bank_{i,t} + \beta_7 Boom_{i,t} * Small\ Bank_{i,t} * High_j + IndustryYear\ FE_{j,t} + CountyIndustry\ FE_{i,j} + CountyYear\ FE_{i,t} + \varepsilon_{i,j,t}$$

	Boom = Log Shale Wells				
	Small Bank = $500M Dummy	Small Bank = $200M Dummy		Small Bank = $1B Dummy	
	Holding Company = Yes	Holding Company = No	Holding Company = Yes	Holding Company = No	Holding Company = Yes
	(1)	(2)	(3)	(4)	(5)
$Boom_{i,t}$			Absorbed by County x Year $FE_{i,t}$		
$High_j$			Absorbed by County x Industry $FE_{i,j}$		
$Small\ Bank_{i,t}$			Absorbed by County x Year $FE_{i,t}$		
$Boom_{i,t}$ * $High_j$	0.001	0.004	0.005	0.003	0.001
	(0.29)	(1.22)	(1.45)	(0.84)	(0.29)
$Boom_{i,t}$ * $Small\ Bank_{i,t}$			Absorbed by County x Year $FE_{i,t}$		
$Small\ Bank_{i,t}$ * $High_j$	-0.008	0.001	-0.004	-0.013	-0.008
	(-1.03)	(0.11)	(-0.56)	(-1.49)	(-1.03)
$Boom_{i,t}$ * $Small\ Bank_{i,t}$ * $High_j$	0.019***	0.014**	0.012*	0.015**	0.019***
	(2.92)	(2.13)	(1.72)	(2.24)	(2.92)
Industry x Year $FE_{j,t}$	Yes	Yes	Yes	Yes	Yes
County x Industry $FE_{i,j}$	Yes	Yes	Yes	Yes	Yes
County x Year $FE_{i,t}$	Yes	Yes	Yes	Yes	Yes
R^2 - Within	0.016	0.013	0.011	0.013	0.016
N	12,764	12,764	12,764	12,764	12,764

Appendix C: Pre-Boom Banking Structure Robustness

This table reports results for a regression form of difference-in-difference-in-differences, where the coefficient of interest is the triple interaction term. This regression is similar to the regression results reported in Table 7, however, the bank size structure of a county is kept the same as the year prior to experiencing a boom. The dependent variable in these regressions is log establishments in county *i* , year *t* , industry group *j* . These specifications provide results for two different measures of Small $Bank_{i,t}$. One measure is a dummy variable, set to 1 if a county has above median small bank branch market share in any given year and 0 otherwise (Small Bank = Dummy), while the other measure is the ratio of branches which belong to small banks relative to the total number of bank branches in a county (Small Bank = Ratio). Additionally, a set of fully saturated interactions between Boom variables, Small Bank variables, and the High external finance dependence dummy are included. The key coefficient of interest for the difference-in-difference-in-differences regression is the triple interaction term β_7. County-industry and industry-year (industry trends) fixed effects are included, as well as county-year fixed effects. Note, reported R squared is close to one, due to the inclusion of multiple high dimensional fixed effects. Standard errors are clustered by county, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

$$Log\ Establishments_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + \beta_2 High_j + \beta_3 Small\ Bank_{i,t} + \beta_4 Boom_{i,t} * High_j + \beta_5 Boom_{i,t} * Small\ Bank_{i,t}$$

$$+ \beta_6 High_j * Small\ Bank_{i,t} + \beta_7 Boom_{i,t} * Small\ Bank_{i,t} * High_j + IndustryYear\ FE_{j,t} + CountyIndustry\ FE_{i,j} + CountyYear\ FE_{i,t} + \varepsilon_{i,j,t}$$

	Boom = Dummy		Boom = Log Shale Wells	
	Small Bank = Dummy	Small Bank = Ratio	Small Bank = Dummy	Small Bank = Ratio
	(1)	(2)	(3)	(4)
$Boom_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
$High_j$	Absorbed by County x Industry $FE_{i,j}$			
Small $Bank_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
$Boom_{i,t}$ * $High_j$	0.013	-0.061	0.004	-0.015
	(0.76)	(-1.43)	(1.02)	(-1.55)
$Boom_{i,t}$ * Small $Bank_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
Small $Bank_{i,t}$ * $High_j$	-0.010	0.020	-0.012	0.008
	(-1.18)	(0.77)	(-1.46)	(0.31)
$Boom_{i,t}$ * Small $Bank_{i,t}$ * $High_j$	0.054*	0.154**	0.014*	0.040**
	(1.80)	(2.12)	(1.91)	(2.31)
Industry x Year $FE_{j,t}$	Yes	Yes	Yes	Yes
County x Industry $FE_{i,j}$	Yes	Yes	Yes	Yes
County x Year $FE_{i,t}$	Yes	Yes	Yes	Yes
R^2 - Within	0.012	0.016	0.012	0.018
N	12,764	12,764	12,764	12,764

Appendix D: Effect of Bank Size and Credit Supply on Establishments of Different Size

(Boom vs. Non-Boom, High Ext Finance Requirements vs. Low Ext Finance Requirements High Small Bank Market Share vs. Low Small Bank Market Share)

This table reports results for the regressions estimated in Table 5 (Difference-in-Differences) and Table 7 (Difference-in-Difference-in-Differences) with outcome measures based on the per capita number of establishments (per 10,000 people) in different size categories. Specifications (1) and (2) are for changes in the number of small establishments (fewer than 10 people). While specifications (3) and (4) are for establishments with more than 10 people. Each outcome variable is scaled by the number of people in a county, and so can be interpreted as establishments per capita in a given size category. Note, reported R squared is close to one, due to the inclusion of multiple high dimensional fixed effects. Standard errors are clustered by county, with t-statistics reported in parentheses below coefficient estimates, where * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

$$Establishments\ Per\ Capita_{i,j,t} = \alpha + \beta_1 Boom_{i,t} + \beta_2 High_j + \beta_3 Small\ Bank_{i,t} + \beta_4 Boom_{i,t} * High_j + \beta_5 Boom_{i,t} * Small\ Bank_{i,t}$$

$$+ \beta_6 High_j * Small\ Bank_{i,t} + \beta_7 Boom_{i,t} * Small\ Bank_{i,t} * High_j + IndustryYear\ FE_{j,t} + CountyIndustry\ FE_{i,j} + CountyYear\ FE_{i,t} + \varepsilon_{i,j,t}$$

	Dependent = Small Est Per Capita		Dependent = Large Est Per Capita	
	Boom = Log Shale Wells		Boom = Log Shale Wells	
	Small Bank = Dummy		Small Bank = Dummy	
	(1)	(2)	(3)	(4)
$Boom_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
$High_j$	Absorbed by County x Industry $FE_{i,j}$			
$Small\ Bank_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
$Boom_{i,t}$ * $High_j$	0.942***	0.145	-0.250	0.028
	(2.76)	(0.44)	(-0.61)	(0.08)
$Boom_{i,t}$ * $Small\ Bank_{i,t}$	Absorbed by County x Year $FE_{i,t}$			
$Small\ Bank_{i,t}$ * $High_j$		-0.339		-0.188
		(-0.39)		(-0.18)
$Boom_{i,t}$ * $Small\ Bank_{i,t}$ * $High_j$		1.421***		-0.493
		(2.92)		(-0.95)
Industry x Year $FE_{j,t}$	Yes	Yes	Yes	Yes
County x Industry $FE_{i,j}$	Yes	Yes	Yes	Yes
County x Year $FE_{i,t}$	Yes	Yes	Yes	Yes
R^2 - Within	0.008	0.015	0.000	0.001
N	12,764	12,764	12,764	12,764