Bank Liquidity, Small Business Lending, and Real Outcomes

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Abstract

Using (a) detailed SBA loan-level data, (b) small business lending from CRA data, and (c) comprehensive National Establishment Time-Series data that covers the universe of small businesses in the U.S., we study the pass-through of bank liquidity gains to small businesses and its implications on business dynamics and jobs. We find novel evidence that when banks receive a positive liquidity shock, they expand credit only to the incumbent or relatively larger small firms, not to new entrants or micro businesses. In line with this, counties receiving a positive liquidity shock experience (1) a higher expansion rate and a lower exit rate for the incumbent small firms, yet a lower growth rate and a higher exit rate among incumbent micro firms, and (2) no changes in the entry rate of new businesses. To establish causality, we exploit time-varying, bank-specific liquidity gains resulting from shale development and focus on businesses in non-shale counties.

JEL: G21, G28, G30, E24, Q40

Keywords: Banks, Small business lending, Business dynamics, Job creation

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I. Introduction

Small businesses are critical to economic growth and job creation. Small firms in the U.S. accounted for 45% of private GDP in 2010 and 63% of new jobs from 1992 to 2013. Despite their importance to the overall economy, small firms continue to face significant obstacles in obtaining external finance. According to the 2016 National Small Business Credit Survey (SBCS) conducted by 12 Federal Reserve Banks, credit availability remains a major challenge for small firms, particularly start-ups. Of the respondents from 0-2-year-old SBCS firms, 72% faced financial challenges, and the ratio falls to 56% for firms that have operated for more than five years. What puzzles policymakers is that despite the massive liquidity injection to the banking sector during the economic recovery period since the 2007-08 financial crisis, credit conditions facing small businesses remain tight: From 2010 to 2013, for example, the share of commercial and industrial (C&I) loans to U.S. small businesses dropped from 29% to 22%, with the approval rate for small business applicants shrinking from 62% to 52%.[1] This raises the key question of whether banks, the main financial intermediaries for small businesses, are indeed effective liquidity providers in funding the investment and growth of these firms.

We study the pass-through of bank liquidity gains to small businesses and its real implications on business dynamics and jobs, using four unique databases: (a) the detailed Small Business Administration (SBA) loan-level data; (b) the Community Reinvestment Act (CRA) data that provides the aggregate loan amount to U.S. small businesses at the bank-county-year level; (c) the comprehensive National Establishment Time-Series (NETS) data that covers the universe of small businesses in the U.S.; and (d) a well database from IHS Markit Energy that covers almost every shale well (over 100,000) drilled in the U.S. Existing studies show that banks affect credit availability to small businesses (Berger, Saunders, Scalise, and Udell, 1998; Strahan and Weston, 1998; Beck, Demirgüç-Kunt, and Maksimovic, 2005; Rice and Strahan,

[1] Based on the 2011 Small Business Finances Poll and Fall 2013 Small Business Credit Survey Report by the Federal Reserve Bank of New York. In line with this, Chen, Hanson, and Stein (2017) shows that small business lending by the four biggest banks falls sharply in recent years.

2010; Berger, Bouwman, and Kim, 2017), and entrepreneurship and the development of small firms (Black and Strahan, 2002; Cetorelli and Strahan, 2006; Kerr and Nanda, 2009). Our study extends the literature in at least three ways. First, we distinguish small firms into micro vs. relatively larger firms, or entrants vs. incumbent firms, and explore the pass-through effects to these different groups. This is an economically important issue, given that micro firms (with less than five employees) and new entrants account for 80% of the total number of businesses in the U.S. in 2013, and employ 23% of people in the economy as a whole.[2] Beck (2013) also stresses that the distinction between micro and small enterprises is critical to the understanding of the transmission mechanisms through which SME finance affects economic development. We find systematic differences in the pass-through effects for different groups of small businesses.

Second, we use two complimentary datasets when examining bank lending to small business: SBA and CRA data. The unique dataset from the U.S. SBA contains detailed loan-level information on more than 1.68 million loans given to eligible small businesses, allowing us to evaluate how bank liquidity gains affect the detailed loan contract terms for these businesses. As the SBA data contain only part of the financing activities to small businesses, we also use CRA data, which contain the bank × county-level lending to small businesses information for all the U.S. bank institutions above certain asset size thresholds that are regulated by the Office of the Comptroller of the Currency, the Federal Reserve System, and the Federal Deposit Insurance Corporation, to test the robustness of the findings. We find consistent empirical results using these two datasets.

Third, we explore the real impact of bank supply of credit resulting from liquidity gains on small business dynamics (i.e., entry, expansion, and exit) and labor market outcomes using the comprehensive NETS dataset. The NETS data provides time-series information on business name, address, contact information, parent company linkage, industry classification, employment, starting year, and years when business was active for the universe of U.S. establishments (about

[2] These numbers are calculated by the authors using all the U.S. establishments based on the NETS data.

58.8 million) during the past two decades. This enables us to construct precise measures of small business entries, expansion, and exits at any granular level we need. In this study, we aggregate business dynamics at county × industry × type (i.e., small firms with different size categories) and examine how bank liquidity gains affect small business dynamics and the associated job creation.[3] We provide novel evidence on the differential effects of bank liquidity gains on business activities for new entrants vs. the incumbents, and small vs. micro firms.

The literature provides valuable insights on why lending outcomes could differ across different types of borrowers (i.e., micro vs. small, and new vs. incumbent) if banks receive a positive liquidity shock. As a traditional type of financial intermediary, banks tend to make lending decisions based on hard information, such as audited financial statements and track records (Petersen and Rajan, 1994; Berger and Udell, 1995; Black and Strahan, 2002). For firms with poor repayment histories or financial statements, banks usually require them to secure their loans with collateral, because this helps alleviate moral hazard and adverse selection problems (e.g., Bester, 1985; Besanko and Thakor, 1987; Aghion and Bolton, 1992; Hart, 1995; Berger, Frame, and Ioannidou, 2011). Another way to overcome information asymmetries and agency problems in the credit market is by the lending relationship developed via multiple transactions, through which banks collect borrower-specific durable and reusable information (Boot, 2000). Small businesses, particularly micro firms and new entrants, usually do not have historical financial statements to track or sufficient collateral to secure the loans, and few have a close lending relationship with the banks. Banks with liquidity gains enjoy an increase in lending capacity, which may alter their lending propensities. For instance, those with a larger lending capacity may divert away from providing micro loans to informationally opaque micro borrowers, and focus on providing relatively larger loans to informationally more transparent small firms. Thus, exploring whether banks pass through their liquidity gains to fund the growth

[3] Most studies use the net change of establishment in a county or a state as a proxy for business entries. This change incorporates information related to both entries and exits. Here we can construct precise measures of entries and exits during the past two decades at a granular level.

and development of small businesses is an empirical question, as is whether banks treat different types of small businesses similarly.

Empirically analyzing the effect of bank liquidity on small business financing and development is challenging, as both bank liquidity and small business dynamics may be affected by economic fundamentals or the expectations of economic conditions. To establish the relationship, we follow Gilje, Loutskina, and Strahan (2016) and use empirical strategies to explore technology driven shocks to the liquidity conditions of individual banks. Specifically, we exploit liquidity windfalls for bank branches resulting from the shale development activities since 2003. In the early 2000s, unexpected technological breakthroughs, known as "fracking," which facilitate shale discoveries and production took the energy sector by surprise. The technological advancements in fracking enable oil and gas companies to extract shale resources in an economically profitable way, triggering large purchases of mineral leases from local property owners in promising areas. These leases typically involve a large upfront bonus based on the number of leased acres plus a royalty percentage on the production from the lease. Landowners who receive large leasing payments usually deposit them into nearby bank branches, thereby generating a positive liquidity shock for banks with branches in these shale counties. To avoid the potential confounding demand side effects and focus on the supply side impact on small business development, we exclude shale counties, i.e., counties with shale development, and include in our sample only counties that did not experience any shale development during the sample period (i.e., non-shale counties).[4]

We begin by constructing a time-varying, bank-specific measure of their exposure to shale liquidity shocks and test the validity of this identification strategy. We first combine (a) comprehensive well data from IHS Markit Energy with (b) detailed information on bank branches from the Federal Deposit Insurance Corporation's (FDIC's) Summary of Deposit. Our key measure, *Shale liquidity shock*, equals the proportion of a bank's branches located in shale

[4] It has been well documented that banks allocate their liquidity among branches through internal capital markets (see, for example, Houston, James, and Marcus, 1997, Gilje, Loutskina, and Strahan, 2016).

counties, where the number of branches in each county is weighted by the number of shale wells drilled in the county multiplied by the bank's market share in that county. Consistent with Gilje, Loutskina, and Strahan (2016), we confirm that deposits grow faster in banks that receive the shale liquidity shock than those that do not receive the shock.

We further construct an instrumental variable, *Shale liquidity shock preexisting branches*, using each bank's branch network and market shares in 2002. This mitigates the concern that banks might alter their branch networks to gain greater exposure to the shale liquidity shock, although the nature of shale development makes it difficult for banks to do so.[5] With respect to the validity of this instrument, not even the energy sector anticipated the advent of fracking before 2003, so banks could not possibly have expected the subsequent shale development back in 2002, suggesting that the instrument satisfies the exclusion restriction. The first-stage results from the 2SLS regressions show that the instrument is strongly and positively correlated with the key measure, *Shale liquidity shock*. The F-statistics on the instrument are way above the conventional threshold, indicating that the weak instrument problem is not a major concern. We conduct 2SLS regressions throughout our analyses unless otherwise indicated.

We find that banks pass through their liquidity gains disproportionately more to relatively larger small businesses and incumbent firms, than to micro firms (fewer than five employees) and new entrants. Specifically, banks that are exposed to the shale liquidity shock originate SBA loans to small or incumbent firms with a larger loan size, and lower interest rates than banks without such exposure. We do not, however, find such a pass-through effect for micro firms or new entrants. The differential effect is of both statistical and economic significance. For example, our estimates suggest that when banks receive a shale liquidity shock equal to one standard deviation of the shocks, the average SBA loan size for the incumbent business applicants (or borrowers with a larger number of employees) would increase by 16% (or 4%-12%) than for

[5] In practice, it is difficult for banks to adjust their branch networks to gain greater exposure to the shale liquidity shock because even oil and gas companies found it extremely challenging to estimate the number of wells an area might need to develop. There is also anecdotal evidence that the mineral lease payments often change very rapidly and significantly during a short term period (Gilje, Loutskina, and Strahan, 2016).

new entrants (or micro firms). These results hold when controlling for bank-county-industry-type fixed effects and county-industry-year fixed effects, together with an array of time-varying bank traits and borrower characteristics. These fixed effects help absorb any unobservable time-invariant county by industry by bank effects, and the time-variant county by industry trends.

As discussed, the SBA data only contains part of the financing activities to small businesses. We therefore use CRA data, which contains the bank × county-level lending information to small businesses for all the U.S. bank institutions above specific asset size thresholds, to test the robustness of the findings. Consistent with our analyses using SBA data, we find that banks that are exposed to the shale liquidity shocks increase their CRA lending only for loans with relative larger dollar amounts— those above $250,000 and below $1 million. This suggests that the majority of micro businesses cannot benefit from banks' positive liquidity gains, as 70% of small businesses in the U.S. seek loans of under $250,000 (Mills and McCarthy, 2016).

Our evidence so far is consistent with the notion that banks with liquidity gains adjust their lending propensities by shifting partially from informationally opaque micro and new borrowers to relatively larger, transparent, and incumbent small firms. If this is the case, it infers a potential deterring effect for new entrants and a crowd-out effect for the incumbent micro firms. We empirically explore these potential real effects using the NETS data. In particular, we assess whether bank liquidity gains and the resulting changes in their lending propensities exert direct impact on the dynamics of different types of small businesses. Using the comprehensive NETS data, we evaluate how the entry, expansion, and exit of different types of small businesses in a non-shale county vary with the extent to which the county receive liquidity shocks.

To do this, we further construct a county-specific liquidity shock measure of the extent to which banks in individual counties receive liquidity shocks through their branches in shale counties. Specifically, we aggregate the liquidity gains to individual banks at the county level, using each bank's market share in small business lending in that particular county as a weight.

We find that county-specific bank liquidity shocks (a) have no significant impact on the entries of small firms, (b) facilitate the expansion of relatively larger incumbents, while dampen the growth of micro ones, and (c) lower the exit rates of larger small firms but expedite the exits of micro firms. The asymmetric effects on new vs. incumbent and micro vs. other small firm are consistent with our previous findings on bank supply of credit to small businesses. These findings suggest that in counties receiving a positive liquidity shock, entrants are deterred from establishing new businesses, and the incumbent micro firms are crowded out by relatively larger small firms. With respect to economic magnitudes, the estimates indicate that in counties that receive liquidity shocks equal to one standard deviation of the cross-county shocks, (a) small businesses with a larger number of employees would grow 23-32 basis points faster than micro firms; and (b) the exit rate of micro businesses is 114 basis points higher while that of other small businesses is 19-57 basis points lower. The difference is equivalent to about 18-23% of the sample mean value of *Business exit*. We find similar patterns when examining job creation from entrants and job loss due to exits. In addition, we show that the effects on the incumbents' expansion and exit rates are larger among industries that rely more heavily on external financing, which is consistent with the notion that bank liquidity shocks affect small business dynamics through the credit channel.

We interpret our findings with caution. By construction, variations in our bank-specific liquidity shock measure come from banks with multiple branches across counties with at least one branch located in shale counties. Thus, our analyses cover relatively large banks with multiple branches, not those very small local community banks. Our study therefore does not address how community banks would react had they received a liquidity gain. However, as relatively large banks are the major liquidity providers in economic activities, their limited lending practices indicate the importance of developing alternative financing vehicles for micro and new start-up firms. This is consistent with the rapid growth of the online "Fintech" platforms such as Internet microloans and peer-to-peer (P2P) lending built on new financial technologies. A good example is the financial firm *Ant Financial* (formerly Alipay), which uses an automated credit rating system built on Alibaba's e-commerce transactional and financial data platform to provide small loans to many small businesses. The payment, sales, procurement, inventory turnover, and logistic data generated by billions of transactions in Alibaba's trading platform Taobao has also helped overcome the information frictions in typical small business lending markets. Since 2010, *Ant Financial* has originated an amount of 1.3 trillion CNY loans to more than 8 million micro businesses. These alternative financing vehicles complement the banking sector and provide essential liquidity to micro firms and new entrants.

The remainder of the paper is as follows. Section II describes the data and variables. Section III introduces the identification strategy and constructs a time-varying bank-specific liquidity shock measure. Section IV presents the empirical results of the effects of bank liquidity shocks on their lending to different types of small businesses, and the resulting small business dynamics. Section V concludes.

II. Data and Variable

To measure small business lending and the associated business dynamics, we use data from three primary sources: (a) the specific contract terms of SBA loans, including loan size and price, from a unique SBA 7(a) dataset; (b) the aggregate lending quantities in the CRA bank-county panel dataset; and (c) small business dynamics based on the comprehensive NETS database that covers the universe of establishments in the U.S. We describe each database in more detail in the following sections.

2.1 SBA 7(a) loans

Small Business Administration (SBA) is an independent agency of the Federal Government that provides services and assistance to small businesses. Their primary goal is encouraging the growth of small businesses and creating jobs. We use contract-level information on 7(a) loans, one of the largest SBA programs, delivered through various methods (e.g., Certified Lenders Program, Preferred Lenders Program, SBA Express, etc.). SBA loan proceeds may be targeted at financing working capital and investment in equipment or real estate. A business applicant must meet the following eligibility requirements: it must fall below a certain employee or sale threshold, i.e., be small enough, making the SBA loans particularly well suited to our study,[6] be organized for profit, and have applied the “Credit Elsewhere Test” demonstrating that it is unable to obtain the loan from any other source. These borrowers thus represent a group of small businesses that rely heavily on the SBA loan scheme to finance their operations and growth. That is, accessibility to SBA finance is crucial to these businesses.

We use a unique version of the SBA 7(a) loan data set over the period 2003-2012, which includes 683,272 SBA loans to eligible small businesses at a total of $137 billion. Our sample period starts from 2003 because this is the first year of shale development facilitated by technological advancement. The 7(a) loan programs provide contract-level data under the SBA. For each loan contract, the data set contains information on the date of approval, the identity and geographic location of the lender and the borrower, the loan size, and spread.

We manually link lenders in the SBA 7(a) data set with banking institutions in the FDIC’s Summary of Deposits (SoD) database. We first conduct a fuzzy match using a lender’s name, street address, city, state, and zip code, followed by a manual check on each matching pair to ensure accuracy. We successfully link 5,239 distinct lenders for 592,784 SBA loans, accounting for 91% of the SBA loans provided by depository banks (i.e., excluding loans provided by non-bank institutions such as credit unions, specialized small business lending corporations, etc.). We further restrict the sample to SBA loans for which borrowers are located in “non-shale” counties, and require the lenders to have all the necessary data for our analyses. Our final sample contains 80% of the SBA loans provided by bank institutions.

We focus on both the quantity and pricing of SBA loans. In particular, *Loan size* equals the log dollar amount of a loan, and *Interest rate* is the loan spread at the time of loan origination. As shown in Table 1 Panel A, the average SBA loan size is $188,000, and the average interest rate equals 7.95%, .

[6] The SBA size standards vary across industry, and change over time. See Small Business Administration (2017) for more detail.

To examine the impact on specific loan terms across different types of borrowers, we distinguish borrowers by size using indicators of borrowers' employee size group (i.e., *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, and *Employee* $\geq$ *10*), or whether they have an established business at the time of loan origination (*Existing business*).

2.2 CRA small business lending

The primary advantage of using SBA loan data is that it contains detailed contract terms, making the empirical testing ground cleaner (as the firms usually do not have other financing arrangements). It has limitations, however, as it only contains part of information on small business financing activities. We therefore use a complementary dataset from the Community Reinvestment Act (CRA) provided by the Federal Financial Institutions Examination Council (FFIEC). The CRA data contains information on the county-aggregate small business credit by each bank in each year. All U.S. bank institutions regulated by the Office of the Comptroller of the Currency, Federal Reserve System, and the Federal Deposit Insurance Corporation, and which meet specific asset size thresholds, must report on an annual basis the aggregate number and dollar amount of small business loans in each origination county.[7] Compared with the SBA data that covers a subset of small business loans, CRA offers a more comprehensive coverage on the county-aggregate volume of small business lending by each bank in each county.

We compile a bank-county panel with more than 725,000 observations on CRA lending during the sample period of 2003-2013. For each bank in a year, we consider the log dollar amount (*Total loan amount*) and the log number (*Total loan number*) of small business loans originated by the bank to each county. CRA further breaks down the lending volume by three loan size categories. We therefore measure *Total loan amount* and *Total loan number* in each of the three loan-size categories: \$100,000 or less, between \$100,000 and \$250,000, and over

[7] The asset size threshold that triggers data collection and reporting for a bank is usually above one billion as of December 31 of either of the prior two calendar years. CRA defines small business loans as those with the original loan amount equal to \$1 million or less and are reported on the bank institution's regulatory financial reports as either "Loans secured by nonfarm or nonresidential real estate" or "Commercial and industrial loans."

$250,000 (and below $1 million), and investigate how banks pass through their liquidity gains to small business lending that falls into each of the three loan-size categories.

As shown in Table 1 Panel B column (1), the average small business lending by a bank in a county is about $3 million, and involves 71 loans. Panel B also reports the summary statistics for two lender groups based on whether a bank receives a positive shale liquidity shock. As shown in columns (2) and (3), the CRA *Total loan amount* originated by banks that received the shock is on average almost twice that of banks that did not receive the shock.

2.3 National Establishment Time-Series (NETS) database

To measure small business dynamics, we utilize a third dataset—National Establishment Time-Series (NETS)—that provides longitudinal information on business name, address, contact information, parent company linkage, industry classification, employment, starting year, and years when business was active for over 58.8 million establishments in the U.S. over the period 1990-2013. The NETS database is a unique establishment-level database that encompasses U.S. businesses, allowing us to construct precise measures on the entry, expansion, and exit of small business and evaluate the real effects of bank liquidity gains on the dynamics of small businesses.

We aggregate small business dynamics at the county-industry-year (or county-industry-type-year) level, where *industry* refers to establishments having the same two-digit SIC code, and *type* indicates whether the number of employees for an establishment falls into 1-2, 3-4, 5-9, or 10 and above. Following the definition of small enterprises in the U.S. Census, we focus on businesses with under 100 employees.[8] Specifically, we calculate (a) *Business entry* as the number of new establishment openings in a year adjusted by the number of existing establishments at the beginning of the year; (b) *Jobs created by entry* as the number of new jobs created from small business entry in a year adjusted by the total number of jobs offered by small businesses at the beginning of the year; (c) *Incumbent employment growth*, equal to the annual

[8] See, for instance, https://www.census.gov/content/dam/Census/library/publications/2015/econ/g12-susb.pdf.

employment growth of incumbent establishments, thus capturing the degree to which small businesses expand and create jobs; (d) *Business exit* as the number of establishment closings in a year scaled by the number of establishments at the beginning of the year; and (e) *Job loss due to exit* as the number of jobs destroyed by establishment closings scaled by the total number of jobs offered by small establishments at the beginning of the year. Table 1 Panel D reports the summary statistics of these business dynamic measures at county × industry × year. As shown, the average entry, expansion, and exit rates of small establishments in a county-industry-year equal 10%, -3.8%, and 7%, respectively. The sample average of *Jobs created by entry* and *Job loss due to exit* equals 7.6% and 6.2%.

2.4 Bank- and county-level characteristics

We account for various bank characteristics using data from the Reports of Condition and Income ("Call Reports") that provide financial statements for each banking institution and FDIC's Summary of Deposits. We include *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, *Cost of funds*, *Log no. branches*, and *Charter type*. All bank-specific financial controls are lagged by a one-year period. When evaluating the effect on small business dynamics, we control for time-varying county traits including *Log population*, *Log income per capita*, *Labor market participation*, and *Proprietorship* using data from the Bureau of Economic Analysis and the Bureau of Labor Statistics. We provide the detailed variable definitions in Appendix Table A1.

III. Identification Strategy

To establish the causal effect of bank liquidity on small business lending and the resultant changes in small business dynamics, we exploit liquidity windfalls for bank branches resulting from the shale development since 2003. We focus on lending outcomes and business dynamics in non-shale counties to mitigate the concerns that our results are affected by changes in local economic conditions due to shale development. This is feasible as it is documented that banks reshuffle their liquidity gains from shale counties to other branches in non-shale counties (Gilje, Loutskina, and Strahan, 2016). In this section, we introduce the background of our identification strategy in more detail, followed by descriptions of the well data, the construction of a bank-specific, the time-varying measure of shale liquidity gains, and the validity test results.

3.1 Fracking and shale development

A technological breakthrough known as fracking occurred in the U.S. gas and oil industry in the early 2000s. By combining horizontal drilling with hydraulic fracturing, fracking makes the production of shale gas economically viable. After two decades of experiments in Barnett Shale Play, Texas, Mitchell Energy initially found that fracking allowed developers to break apart the highly non-porous rock of shale formations, freeing the natural gas trapped inside the rock (Yergin, 2011; Gold, 2014). The Barnett Shale began to produce vast quantities of shale gas after Devon Energy bought Mitchell Energy and combined slick-water fracking with horizontal drilling in late 2002, and fracking reached its full potential. We therefore treat 2003 as the first year when oil and gas companies started large-scale shale development activities.

The technological developments of fracking have changed the conventional wisdom on shale gas production and the energy landscape in the U.S. According to the Energy Information Administration's Annual Energy Outlook (AEO 2016), shale gas accounts for nearly half the total U.S. natural gas production in 2015, and has become the nation's leading source of nonconventional energy. In contrast, the share of hydrocarbon produced from shale wells was less than 1% in 1999, when shale production was not commercially viable. The technological advancements that facilitate shale development enable the U.S. to exploit the country's vast amount of usable shale reserves: about 200 trillion cubic feet (tcf) of proven shale gas resources, and an estimated 623 tcf of additional unproven yet technically recoverable shale gas resources.[9]

[9] See https://www.eia.gov/energyexplained/index.cfm?page=natural_gas_where.

This combined 823 tcf of shale gas is enough to fulfill the entire nation's gas consumption for at least 30 years.

The technological advancements in shale discoveries led oil and gas companies to begin purchasing mineral leases from local landowners to conduct drilling operations. These leases typically involve a large upfront bonus based on the number of acres leased plus a royalty, depending on extracted resources from the lease. Property owners who received large leasing payments then deposit into local bank branches, leading to a positive liquidity shock for these branches.

The liquidity windfalls resulting from shale development were material for local bank branches. Anecdotal evidence suggests that leasing contracts use an average bonus of $15,005 per acre, plus an average royalty of 17.5% (Plosser, 2015). A property owner who leases out one square mile of land (equivalent to 640 acres) at the average lease rate would receive an upfront payment of $9.6 million plus future monthly royalties. Consistent with the research (Gilje, Loutskina, and Strahan, 2016), we provide empirical evidence in Section 3.3 that formally validates this setting: banks exposed to shale development experience a material increase in deposit growth.

Shale-induced windfalls generate positive liquidity shocks that are plausibly exogenous to banks for three main reasons. First, the technological advances in fracking were unanticipated, and according to Chevron CEO John Watson "took the industry by surprise." Second, given that extracting shale gas is difficult and expensive (Lake et al., 2013), the economic viability of developing shale is often driven by broader macroeconomic factors, such as demand for and prices of natural gas, not local economic conditions (Gilje, Loutskina, and Strahan, 2016). Third, the features of shale development make it difficult for banks to alter their branch networks to gain greater exposure to shale windfalls: (a) it is challenging even for the oil and gas companies to estimate the number of wells an area might need to develop; and (b) mineral lease payments often change very rapidly and significantly over a short period (Gilje, Loutskina, and Strahan, 2016). We further mitigate this last concern by constructing an instrument using each bank's branch networks in 2002, which is before the technological innovations and the onset of shale development. We describe our instrumental variable in the next section.

3.2 Well data and bank-specific shale liquidity shock measures

To construct a time-varying, bank-specific shale liquidity shock measure, we combine the well data from IHS Markit Energy with the bank branch data from the Federal Deposit Insurance Corporation's (FDIC's) Summary of Deposits (SoD). IHS Markit Energy offers a unique well database, which covers more than 100,000 shale wells drilled in the U.S. over the period 2003-2013. A 14-digit American Petroleum Institute (API) number uniquely identifies each well in the database, and detailed information on the spud date, location, and orientation of each well is provided. For each bank branch in a year, the FDIC's SoD contains detailed information on its affiliated bank institution, geographic location, and deposit balances.

We first calculate the number of shale wells drilled in each county during a year using the IHS well data.[10] $Wells_{jt}$ represents the number of shale wells drilled in county *j* from 2003 to year *t*. The top panel of Figure 1 plots the spatial distribution of the intensity of shale development across U.S. counties over the sample period of 2003-2013. We then use bank branch data from SoD to determine the number of branches and the amount of deposits held by each bank in each county in a year. Our time-varying, bank-specific liquidity shock measure equals the proportion of a bank's branches that are located in shale counties, and the number of branches in each shale county are weighted by the intensity of liquidity windfalls received by the bank in the county. Formally, our key measure is defined as follows.

$$Shale\ liquidity\ shock_{b,t} = \sum_j \left(Branches_{b,j,t} * Wells_{j,t} * Mktshr_{b,j,t}\right) / Branches_{b,t}, \quad (1)$$

[10] Following the research, we treat horizontal wells as shale wells, as horizontal drilling is the key element in the technologies of drilling shale wells. According to Gilje, Loutskina, and Strahan (2016), almost all horizontal wells in the U.S. are drilled to extract shale or other unconventional oil and gas resources.

where b, j, and t represent bank, county, and year, respectively. $Branches_{b,j,t}$ denotes the number of branches owned by bank b in county j in year t; $Branches_{b,t}$ denotes the total number of branches owned by bank b in year t; $Wells_{j,t}$ is the number of shale wells drilled in county j from 2003 as of year t; and $Mktshr_{b,j,t}$ equals the share of deposits in county j in year t that are held at bank b's branches in county j. Assuming that liquidity windfalls received by bank b in a county j is proportional to (a) the intensity of shale discoveries in the county, and (b) the bank's market share in that county, we weight bank b's number of branches in county j by $Wells_{j,t} * Mktshr_{b,j,t}$. *Shale liquidity shock* is therefore constructed to capture a bank's exposure to positive liquidity shocks through its branch networks in shale counties. Note that *Shale liquidity shock* equals zero for (a) all bank-years before 2003 when technological advances in fracking first occur, and (b) banks without any branches located in shale counties. Table 1 Panel C shows that the sample average *Shale liquidity shock* equals 0.5 across all bank-years and 2 among bank-years that received positive liquidity shocks.

As emphasized above, we further construct an instrument for *Shale liquidity shock* to mitigate the concern that banks might alter their branch networks to gain greater exposure to shale liquidity shocks, although the nature of the shale development process makes it very unlikely that they will do so. We construct the instrument in a similar way to that for *Shale liquidity shock*, except we use each bank's branch structure in 2002, the year before the technological breakthroughs that enabled large-scale shale development. The banks could not have expected the subsequent shale development back in 2002, as not even the energy sector anticipated the advent of fracking before 2003. The instrument is defined as follows.

$$Shale\ liquidity\ shock\ preexisting\ branches_{b,t} = \sum_j \left(Branches_{b,j,2002} * Wells_{j,t} * Mktshr_{b,j,2002}\right) / Branches_{b,2002}, \quad (2)$$

where b, j, t, and $Wells_{j,t}$ are defined the same as in Equation (1). $Branches_{b,j,2002}$ denotes the number of branches owned by bank b in county j in 2002; $Branches_{b,2002}$ denotes the total number of branches owned by bank b in 2002; and $Mktshr_{b,j,2002}$ equals the share of total deposits in county j in year 2002 that are held by bank b in county j. For each bank, *Shale liquidity shock preexisting branches* only captures cross-county, cross-time variations of the shale development activities, not changes in a bank's branch networks over time. We use *Shale liquidity shock preexisting branches* as the instrument for *Shale liquidity shock* in our 2SLS regressions.

Several factors suggest that the instrument satisfies both the relevance and exclusion restrictions. First, with respect to the exclusion restriction, to the extent that banks could not have anticipated the shale boom back in 2002, our instrument is plausibly orthogonal to bank characteristics that might be correlated with their lending decisions. Second, we note that the first-stage regression results of our 2SLS analyses below (i.e., Table 2 column (1)) show that the coefficient estimate on *Shale liquidity shock preexisting branches* is positive and statistically significant at the 1% level, with the F-statistic on the instrument equal to 863 and thus easily passing the weak instrument tests.

3.3 Validity tests

The key assumption underlying our identification strategy is that shale development brings liquidity windfalls for local bank branches, as property owners tend to deposit their leasing payments into local branches. We formally test this channel using the following regression models.

$$Deposit\ growth_{b,t} = \varphi_0 + \varphi_1 Shale\ liquidity\ shock_{b,t} + \varphi_2{}'\Pi_{b,t-1} + \alpha_b + \alpha_t + \varepsilon_{b,t}, \quad (3)$$

where b and t represent bank and year. The dependent variable, $Deposit\ growth_{b,t}$, is the growth rate of deposits (either *Total deposits*, *Retail deposits*, *Time deposits >$100k*, or *Brokered deposits*) of bank b in year t. The key explanatory variable, $Shale\ liquidity\ shock_{b,t}$, is the bank-specific liquidity shock measure defined in Equation (1). We also include various one-year-lagged bank traits: *Log assets*, *Equity ratio*, *Liquid assets*, *Wholesale funding*, *C&I loans*, *Tier 1* *ratio*, *Cost of funds*, *Log no. branches*, and *Charter type* ($\Pi_{b,t-1}$), and bank (α_b) and year (α_t) fixed effects to account for unobservable, time-invariant factors across banks and the overall time trends. We estimate the model using both Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS), with standard errors two-way clustered at the bank and year level.

As can be seen from Table 2 column (1), the first-stage results from 2SLS regressions show that the instrumental variable, *Shale liquidity shock preexisting branches*, is strongly and positively correlated with *Shale liquidity shock*, demonstrating the validity of our instrument. The remaining columns of Table 2 show strong and robust results suggesting that deposits grow faster in banks receiving a positive liquidity shock than banks that do not receive the shock. As shown in column (2) and (3), *Shale liquidity shock* enters both the OLS and 2SLS regressions positively and significantly at the 1% level. The economic magnitude is large. The coefficient estimate on *Shale liquidity shock* in column (2) suggests that deposits would grow 2 (= 2.593*0.008) percentage points faster in banks that received an average level of *Shale liquidity shock* (= 2.593) than banks that did not receive the shock. This is equivalent to about 19% of the sample mean of *Total Deposit growth* (10.7 percentage points). This magnitude is also similar to that found by Gilje, Loutskina, and Strahan (2016) who show that deposits would grow 2.5 percentage points faster for banks exposed to the shale boom than unexposed banks.

In addition, we evaluate whether the deposit-increasing effects of the shale liquidity shock vary across different types of deposits in a predictable manner. If shale liquidity windfalls result from property owners depositing their leasing payments into local bank branches, the effects should be significant among retail and time deposits, but not brokered deposits (those deposits accepted by a bank from or through the mediation or assistance of a third party, such as a person or company or organization other than the owner of the deposit). We test this conjecture by repeating the OLS and 2SLS regressions in columns (2) and (3), while replacing the dependent variable with the growth rate of three types of deposits: (a) *Retail deposits*, (b) *Time deposits of $100,000 or more*, and (c) *Brokered deposits*.

Consistent with our expectations, we find that positive shale liquidity shocks significantly increase the growth of *Retail deposits* and *Time deposits of $100,000 or more*, not *Brokered deposits*. As reported in columns (4)-(9), the coefficients on the instrumented *Shale liquidity shock* are positive and statistically significant at the 1% level in the regressions of *Retail deposits* and *Time deposits of $100,000 or more*, but insignificant in the regressions of *Brokered deposits*. Taken together, the results in Table 2 are consistent with the anecdotal evidence that the shale development activities bring positive and material liquidity windfalls for local bank branches.

IV. Results

In this section, we present and discuss the empirical results of the pass-through of bank liquidity gains to small business lending, and its subsequent effect on small business dynamics. Depending on the outcome variables, we conduct the analyses at different levels. We describe each model specification in greater detail before discussing the corresponding results.

4.1 SBA loan outcomes

We start our analyses by evaluating the pass-through effects of bank liquidity gains on specific loan terms. We explore the average pass-through effects, and the differential effects on different types of borrowers, i.e., firms with different employee size, or entrants vs. incumbent firms. The model specification at the loan-level is as follows.

$$SBA_{l,b,f,j,i,type,t} = \beta_0 + \beta_1 Shale\ liquidity\ shock_{b,t}\ (+\beta_2 Shale\ liquidity\ shock_{b,t} * Type) \\ +\beta_3{}'\Pi_{b,t-1} + \beta_4{}'\Theta_{f,t} + \alpha_{b,j,i,type} + \alpha_{j,i,t} + \varepsilon_{l,b,f,j,i,type,t}, \quad (4)$$

where the dependent variable, $SBA_{l,b,f,i,j,type,t}$, represents the specific loan term (*Loan size*, or *Interest rate*) for SBA loan *l* originated by bank *b* to borrowing firm *f* that belongs to group *type* in industry *i* in county *j* in year *t*. *Type* denotes either *Existing business* (an indicator of whether borrower *f* has already established its business at the time of loan origination) or a set of indicators of borrower *f*'s employee size (i.e.,, *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, and *Employee* $\geq$ *10*). *Shale liquidity shock*$_{b,t}$ is the same bank-specific liquidity shock measure as defined in Equation (1). Thus, β_1 estimates the average effects of bank liquidity gains to SBA loan terms. When we assess the pass-through effects on different types of borrowers, we further add in the interactions between *Shale liquidity shock*$_{b,t}$ and indicators of borrowers' *Type*. In this case, β_1 estimates the pass-through effects of bank liquidity gains to the SBA loan terms for new entrants (or micro businesses, i.e., firms with one or two employees), and β_2 captures the differences in the pass-through effects between entrants and incumbent firms (or micro and small business). $\Pi_{b,t-1}$ denotes a set of one-year-lagged bank traits including *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, *Cost of funds*, *Log no. branches*, and *Charter type*, and $\Theta_{f,t}$ denotes a set of borrower characteristics including indicators of *Business organization* (proprietorship, partnership, or corporation), indicators of employee size, and/or an indicator established business. We include bank-county-industry-type fixed effects ($\alpha_{b,j,i,type}$) to account for any unobservable, time-invariant factors across banks, borrower counties, industries, and types, together with county-industry-year fixed effects ($\alpha_{j,i,t}$) to condition out time-varying factors across county-industries. Our loan-level analyses thus compare the loan terms provided by otherwise similar banks except for receiving different degree of shale liquidity shocks.

We focus on SBA loans for which the borrowers are located in non-shale counties (i.e., counties with no shale discoveries), to mitigate the concern that our results are affected by changes in local economic conditions and thereby the demand side of credit due to shale development. We estimate Equation (4) using 2SLS, where *Shale liquidity shock* (and *Shale liquidity shock * Type*) is instrumented with *Shale liquidity shock preexisting branches* (and *Shale liquidity shock preexisting branches * Type*), with the standard errors clustered at the bank and year level. We report the results in Tables 3 and 4.

We find that banks pass on their liquidity gains only to small or incumbent firms, but not to micro businesses or new entrants. When examining SBA *Loan size*, Table 3 column (1) shows that the coefficient on *Shale liquidity shock* is positive and statistically significant at the 1% level, suggesting that the average SBA loan size increases following a shale liquidity gain. Columns (2) and (3) show that the interaction term, *Shale liquidity shock * Existing business*, enters positively and significantly at the 1% statistical level, whereas the linear term, *Shale liquidity shock*, enters insignificantly. These results suggest that banks exposed to the shale liquidity shock would originate larger size loans to small incumbent firms. We do not, however, find similar pass-through effects for new entrants.

With respect to the effects on small firms with different employee size categories, Table 3 columns (4) and (5) show that the coefficient estimates on *Shale liquidity shock* are statistically insignificant, implying no significant impact on SBA loan size for micro firms, i.e., firms with one or two employees. In contrast, the coefficients on the interactions of *Shale liquidity shock*, and *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, and *Employee* $\geq$ *10* are all positive and significant, indicating that when banks receive a liquidity gain, they would increase the SBA loan size disproportionately more for relatively larger small businesses than for micro firms. The results are robust to the inclusion of (a) bank-county-industry-type and county-industry-year fixed effects, and (b) bank and borrower characteristics.

The differences in the pass-through effects between the incumbents and entrants (small and micro firms) are economically large. Coefficients from the most stringent model, Table 3 column (3) (column (5)), indicate that when lenders receive liquidity gains equal to one standard deviation of the shocks (*Shale liquidity shock* = 2.2), the SBA loan size would increase disproportionately more for incumbent firms (firms with a larger number of employees) by 16% (4%-12%), than for new entrants (micro firms).

We find consistent results when examining the loan price, as reported in Tables 4. Using the same specification as in Equation (4) with *Interest rate* as the dependent variable, Table 4 suggests that banks receiving liquidity gains would pass it through only to particular types of borrowers via loan price. As shown in Table 4, the linear term, *Shale liquidity shock*, enters insignificantly in column (1), suggesting no significant changes in the average loan spread.

However, columns (2)-(5) show that the interaction of *Shale liquidity shock* and indicators of borrower type enters negatively and significantly. In particular, while the linear term of *Shale liquidity shock* enters insignificantly in columns (2) and (3), its interaction with *Existing business* enters negatively and significantly. In a similar way, while *Shale liquidity shock* is estimated to be insignificant in columns (4) and (5), coefficients on its interaction with *Employee* $\in$ *[5,9]* and *Employee* $\geq$ *10* are negative and statistically significant. Combined together, these results suggest that the incumbents or firms with five employees or more obtain SBA loans with lower interest rates had lenders received a positive shale liquidity shock. With regard to the economic magnitude, coefficient estimates from Table 4 column (3) (column (5)) suggest that when banks receive a one-standard-deviation of the shale liquidity shocks (*Shale liquidity shock* = 2.2), *Interest rate* for the incumbents (firms with five employees and above) would be 22 (14) basis points lower than that of entrants (micro firms). This is equivalent to about 9.5% (5.8%) of the standard deviation of *Interest rate* in our SBA loan sample.

Taken together, Tables 3 and 4 provide loan-level evidence suggesting that banks pass their liquidity gains disproportionately more to relatively larger or incumbent small businesses than to micro firms or entrants. This is consistent with the notion that banks receiving liquidity gains adjust their lending propensities by partially shifting from offering credit to micro and new borrowers that can be informationally opaque, to relatively larger and incumbent small firms, which are comparatively more transparent.

4.2 Aggregate small business lending

We next use CRA data, which offers information on small business lending at the bank × county level for all the U.S. bank institutions above certain asset size thresholds.[11] The model specification we use to investigate how banks' exposure to the shale liquidity shock affects their small business lending volume in non-shale counties is as follows.

[11] As mentioned, compared with the SBA data that covers a subset of small business loans, CRA provides a more comprehensive coverage on small business lending originiated by each bank in each county.

$$CRA_{b,j,t} = \varphi_0 + \varphi_1 Shale\ liquidity\ shock_{b,t} + \varphi_2{}'\Pi_{b,t-1} + \alpha_{b,j} + \alpha_{j,t} + \varepsilon_{b,j,t}. \quad (5)$$

The unit of analysis is at the bank-county-year level. The dependent variable, $CRA_{b,j,t}$ represents either *Total loan amount* or *Total loan number* originated by bank *b* in non-shale county *j* during year *t*. *Shale liquidity shock*$_{b,t}$ and $\Pi_{b,t-1}$ are defined the same as in Equation (4). We also include bank-county fixed effects ($\alpha_{b,j}$) and county-year dummies ($\alpha_{j,t}$) to condition out any time-invariant differences across bank-county pairs and time-varying factors across counties (such as local economic conditions), respectively. As noted in Section 2.2, CRA further breaks down small business lending into three loan-size categories: $100,000 or less, between $100,000 and $250,000, or more than $250,000. Thus, we estimate the pass-through effects of bank liquidity gains on their small business lending in each loan-size category. We continue to estimate the model in Equation (5) using 2SLS where *Shale liquidity shock* is instrumented with *Shale liquidity shock preexisting branches*, with the standard errors two-way clustered at the bank and year level.

The results reported in Table 5 are consistent with our loan-level findings. We find that banks receiving liquidity windfalls increase the amount of small business loans only for those falling into the largest size category. As shown in columns (5) and (6), our bank-specific liquidity gains measure, *Shale liquidity shock*, enters positively and significantly at the 1% level for small business lending with loan size above $250,000. The economic magnitude is not small. The coefficients in columns (5) and (6) indicate that banks exposed to a shale liquidity shock equal to one standard deviation of the shocks would increase the dollar amount and the number of small business loans in the largest category by about 15.8% (= 0.072*2.2) and 3.5% (= 0.016*2.2), respectively. In contrast, the coefficients on *Shale liquidity shock* are statistically insignificant and economically small for the other two categories with loan size below $250,000, as reported in columns (1)-(4).

To the extent that the loan size reflects the size of the borrowing business, the results in Table 5 are consistent with the notion that banks pass through their liquidity gains to relatively larger small firms, but not to micro firms. These results further imply that the majority of small businesses cannot benefit from banks' positive liquidity gains, as 70% of small business in the U.S. seek loans under $250,000 (Mills and McCarthy, 2016).

4.3 Small business dynamics

Our evidence so far suggests that banks pass through their liquidity gains disproportionately to certain types of borrowers. If this is indeed the case, then the shifts in bank lending propensities should exert direct impact on small business dynamics and the associated job implications. We test the predictions on business dynamics using the comprehensive establishment-level data from NETS. Specifically, we evaluate how the entry, expansion, and exit of micro vs. small businesses in a non-shale county vary with the extent that banks in the county receive shale liquidity shocks through their branch networks in shale counties.

We further construct a county-specific measure of the degree to which banks in each county receive liquidity shocks. For each county in a year, we calculate *Shale liquidity shock*^{County} as the weighted average of *Shale liquidity shock* across banks in each county, where each bank is weighted by its share of small business lending in that particular county. Formally,

$$Shale\ liquidity\ shock^{County}{}_{j,t} = \sum \omega_{b,j,t} * Shale\ Liquidity\ shock_{b,t}. \quad (6)$$

Shale liquidity shock$^{County}{}_{j,t}$ denotes the extent to which banks in county j receive shale liquidity shocks in year t. $\omega_{b,j,t}$ equals the amount of small business lending originated by bank b in county j in year t, as a share of the total amount of small business lending across all banks in county j in year t based on the CRA data; *Shale liquidity shock*$_{b,t}$ is the same bank-specific liquidity shock measure defined in Equation (1). Thus, *Shale liquidity shock*^{County} captures the degree of liquidity gains received by banks in a non-shale county through their branch networks in shale counties. The bottom panel of Figure 1 (red areas) plots the geographic distribution of the county-specific liquidity shock measure, *Shale liquidity shock*^{County}. As shown, the county-specific liquidity shock varies substantially across the U.S. counties and does not exhibit any regional clustering. The blue areas in the figure represent counties with shale development (the same as in the top panel of Figure 1), which are excluded from our sample.

Using the same procedure, we construct the instrument for the county-specific liquidity shock. We define the county-specific instrumental variable as follows.

$$Shale\ liquidity\ shock\ preexisting\ branches^{County}{}_{j,t} = \sum \omega_{b,j,2002} * Shale\ Liquidity\ shock\ preexisting\ branches_{b,t}, \quad (7)$$

where *Shale liquidity shock preexisting branches*$^{County}{}_{j,t}$ denotes the extent to which banks in county *j* receive shale liquidity shocks in year *t* based on preexisting bank branch networks back in 2002; $\omega_{b,j,2002}$ is the share of small business lending originated by bank *b* in county *j* in 2002 based on the CRA data; and *Shale liquidity shock preexisting branches*$_{b,t}$ has the same definition as in Equation (2).

To evaluate the effects of liquidity shocks on the dynamics of small businesses, we estimate the following model specification at the county × industry (× type) × year level.

$$Dynamics_{j,i,(type,)t} = \theta_0 + \theta_1 Shale\ liquidity\ shock^{County}{}_{j,t} + (\theta_2' Shale\ liquidity\ shock^{County}{}_{j,t} * Type) + \theta_3' \mathrm{H}_{j,t-1} + \alpha_{j,i}(\alpha_{j,i,type}) + \alpha_{i,t} + \varepsilon_{j,i,(type,)t}, \quad (8)$$

where the dependent variable, *Dynamics*$_{j,i,(type,)t}$, represents one of the measures of small business dynamics (i.e., *Business entry*, *Jobs created by entry*, *Incumbent employment growth*, *Business exit*, and *Job loss due to exit*) in county *j*, industry *i*, (group *Type*,) and year *t*. Similar to the analyses above, *Type* denotes a series of indicators of an establishment's employee size (i.e.,, *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, and *Employee* $\geq$ *10*). The explanatory variable, *Shale* *liquidity shock*$^{County}{}_{j,t}$, is the county-specific liquidity shock measure as defined in Equation (6). When evaluating how the effects of county liquidity shocks on business dynamics vary with different business size, we add in the interactions between *Shale liquidity shock*$^{County}{}_{j,t}$ and business size indicators (i.e., *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, and *Employee* $\geq$ *10*). In this case, θ_1 captures the effects of county liquidity gains on the dynamics of micro businesses (firms with one or two employees), and β_2 captures the differential impact on small firms with larger employee size. $\mathrm{H}_{j,t-1}$ represents a set of one-year-lagged county-specific traits, namely *Log population, Log income per capita, Labor market participation*, *Proprietorship*, *Log No. Local Branches*, and *Small business lending HHI*, and an array of bank characteristics averaged at the county level, including the weighted average of *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio* and *Cost of funds*. We further include county by industry ($\alpha_{j,i}$) (or county by industry by type ($\alpha_{j,i,type}$)), and industry by year fixed effects ($\alpha_{i,t}$) to condition out any time-invariant differences across county-industries (or county-industry-type), and time-varying differences across industries.

As highlighted above, we focus on small businesses in non-shale counties only. We estimate Equation (8) using 2SLS with *Shale liquidity shock preexisting branches*^{County} (and *Shale liquidity shock preexisting branches*^{County} * *Type*) as the instruments for *Shale liquidity shock*^{County} (and *Shale liquidity shock*^{County} * *Type*). Standard errors are two-way clustered at the county and year level. We report the results in Table 6-9.

We find that the county-specific liquidity shock influences small business dynamics and the related labor market outcomes in a way consistent with our previous findings. The results presented in Table 6 indicate that the county liquidity shocks do not have a significant effect on the entries of small or micro businesses. As shown, *Shale liquidity shock*^{CountyAgg}, and its interaction with employee size indicators enter insignificantly in all specifications, suggesting that county liquidity shocks have a very limited impact on (a) the creation of small businesses, and (b) the associated job creation. This is consistent with our loan-level analyses, suggesting that banks do not pass through liquidity gains to new entrants, thus having no effect on the creation of new businesses.

Focusing on the incumbents, Table 7 suggests that small businesses with a larger number of employees would grow disproportionately faster in counties where banks receive a positive liquidity gain. As reported in columns (2) and (3), The interactions of *Shale liquidity shock*^{County}, and *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, or *Employee* $\geq$ *10*, enter positively and significantly at the 1% level, whereas the linear term of *Shale liquidity shock*^{County} enters negatively and significantly, suggesting that county liquidity shocks promote the employment growth for the incumbents that are relatively larger, but stifle the expansion of micro firms. This is again consistent with our loan-level findings on the disproportionate pass-through effects on small vs. micro businesses. Column (1), however, shows that the county liquidity shock is not significantly associated with the incumbents' overall employment growth rate in a county.

The economic magnitude is meaningful. The coefficient estimates from Table 7 column (3) indicate that small firms that employ three or four (five to nine, or ten and above) people would grow 23-32 basis points faster than micro firms with one or two employees in counties receiving a liquidity shock equal to one standard deviation of the shocks.

Table 8 further suggests that the county-specific liquidity shocks directly affect the exit of small businesses, in a manner consistent with our previous findings. As shown in columns (2) and (3), the coefficients on *Shale liquidity shock*^{County} are estimated to be positive and significant. In contrast, those on the interactions of *Shale liquidity shock*^{County} and *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, or *Employee* $\geq$ *10* are negative and significant. This finding suggests that county liquidity shocks lower the exit rates of small firms but expedite the exits of the micro firms. When looking into *Job loss due to exit*, we find similar patterns as shown in columns (5) and (6). Columns (1) and (4) further show that the average effects of county liquidity shock on business exit and the resultant job destruction are not significant.

The coefficient estimates from Table 8 column (3) suggest that in counties receiving a one-standard-deviation-greater liquidity shock, the exit rate of small businesses with three or above employees is 19-57 basis points lower, whereas that of micro businesses is 114 basis points higher. Thus, in counties receiving a liquidity shock equal to one standard deviation of the shocks, firms with a larger size would exit slower than micro firms by 133-171 basis points, which is equivalent to about 18-23% of the sample mean value of *Business exit* (0.074).

Combined together, our findings suggest a “crowd-out” effect on small business dynamics: in counties receiving a positive liquidity shock, incumbent micro firms suffer from a significant decline in the growth rate and a higher exit rate, whereas relatively larger firms benefit from a faster expansion rate and a drop in business exit.

In addition, we investigate whether the effects of liquidity gains on small business dynamics vary with industrial dependence on external finance. If the effects on business activities are associated with bank credit supply, then the effects should be particularly pronounced among industries that rely heavily on external source of financing. To test this, we employ the strategy in Rajan and Zingales (1998) and partition the sample based on whether an industry’s external finance dependence (EFD) is below or above the sample quartile.

We re-run the model specifications similar to Table 7 and 8 for the below-bottom-quartile, and above-top-quartile industrial EFD subsamples, and report the results in Table 9. As shown, the effects of liquidity gains on the incumbents’ expansion and exit rates are larger among industries that need more external financing. This is consistent with our interpretation that bank liquidity shocks affect small business dynamics through the credit channel.

V. Conclusion

In this study, we investigate the pass-through of bank liquidity gains to different types of small businesses and its real implications on small business dynamics and jobs. We distinguish small firms into micro vs. relatively larger firms, or entrants vs. the incumbents. To establish causality, we exploit exogenous liquidity gains for local bank branches resulting from the shale development since 2003, to construct a time-varying, bank-specific measure of the extent to which a bank receives shale liquidity shocks through its branches in shale counties. We focus on outcomes in "non-shale" counties, i.e., those without shale discoveries, to mitigate the concerns that our results are driven by changes in local economic conditions due to shale development.

Using (a) the detailed SBA loan-level data and (b) the CRA bank × county-level lending information on small businesses, we find that banks pass through the positive liquidity shocks disproportionately to the incumbents and firms with a larger size, but not to new entrants or micro firms. Consistent with this, we further discover that shifts in bank lending propensities affect small business dynamics. Using the comprehensive NETS data that covers the universe of the U.S. establishments, we find that the county-specific liquidity shocks (a) exert insignificant effect on the creation of new firms and jobs created by entrants, (b) promote incumbents' employment growth only for those relatively larger firms, while stifle the expansion of micro firms, and (c) reduce the exits of small firms but expedite the exits of micro firms. The evidence collectively suggests that banks have limitations in financing micro and new start-up firms, and that a positive liquidity shock could shape business activities in a way that micro firms are ultimately crowded out by other small firms.

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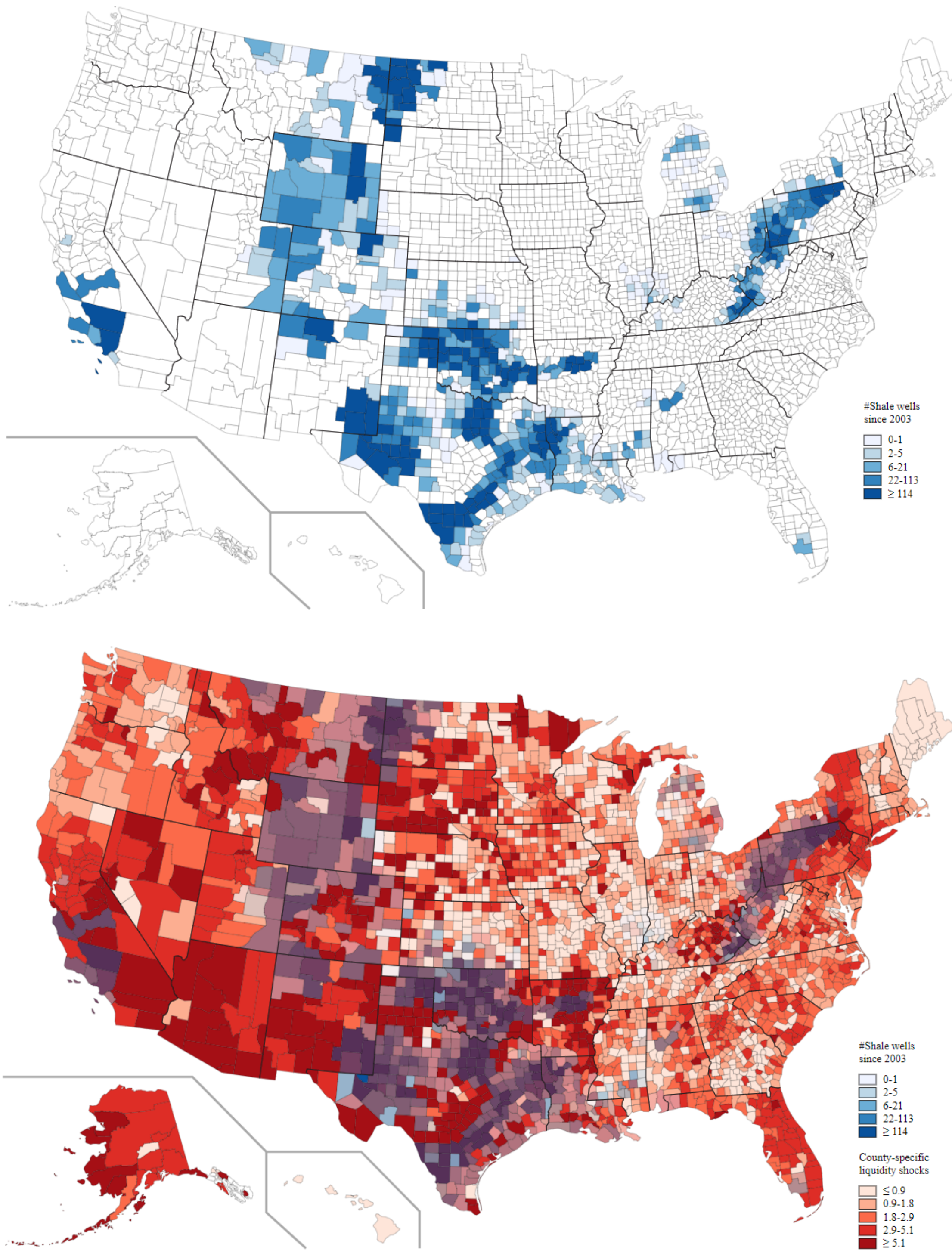

Figure 1. Shale Development vs. Shale Exposure via Bank Branch Networks, by U.S. County in 2013

Note: Blue areas in both the top and bottom panels represent the number of actual shale wells drilled in each county over the period of 2003-2013; red areas in the bottom panel represent the county-specific measure of the degree to which banks in each county receive liquidity shocks through their branch networks in shale counties. Darker colors indicate higher values.

Table 1: Summary Statistics

This table reports summary statistics of the key variables used in this study. We report sample mean values throughout the table, with sample standard deviations in the parentheses. Figures in Column 1 correspond to summary statistics for the whole sample. Columns 2 and 3 report the summary statistics when either dividing banks based on whether they receive positive shale liquidity shocks or not (Panel A, B, and C), or non-shale counties by the degree to which their banks are exposed to liquidity shocks through their branches in shale counties (Panel D and E). Panel A reports the statistics of the SBA 7a loan characteristics, including loan size and interest rate. Panel B reports the statistics of the total dollar amount and the total number of loans for CRA small business lending by each bank to each county. Panel C reports the statistics of the shale liquidity shock along with bank-specific characteristics among SBA lenders. Panel D reports the statistics of the degree to which banks in a county receive liquidity shocks through their branch networks in shale counties, *Shale liquidity shock*^{County}, and the small business dynamics, namely the creation of new establishments, news jobs created by entrants, the employment growth of the incumbents, the exit of establishments, and the job loss due to business exit. We focus on establishments with employee size below 100 that are not branches or subsidiaries of a parent entity, a foreign-owned company, or a public firm, using the NETS data.

	Whole Sample	Shale-Exposed Banks	Unexposed Banks
	(1)	(2)	(3)
Panel A. SBA Lending (Loan Level)			
Loan Size ($k)	188	151	234
	(358)	(314)	(402)
Interest Rate (percentage)	7.95	8.54	7.19
	(2.36)	(2.56)	(1.84)
Obs.	473,433	263,726	209,707
Panel B. CRA lending (Bank-County-Year Level)			
Total Loan Amount ($k)	2,968	4,107	2,292
	(13,954)	(18,271)	(10,533)
Total Loan Number	71	49	84
	(434)	(340)	(481)
Obs.	725,745	270,255	455,490

Table 1: Summary Statistics (Continued)

	Whole Sample	Shale-Exposed Banks	Unexposed Banks
	(1)	(2)	(3)
Panel C. Bank Characteristics (Bank-Year)			
Shale Liquidity Shock	0.486	2.593	0.000
	(2.239)	(4.614)	(0.000)
Total Deposit Growth	0.107	0.104	0.107
	(0.772)	(0.325)	(0.842)
Log Assets	12.107	12.615	11.990
	(1.313)	(1.671)	(1.185)
Equity Ratio	0.104	0.104	0.104
	(0.040)	(0.040)	(0.039)
Liquid Assets	0.264	0.291	0.258
	(0.138)	(0.155)	(0.133)
Deposits	0.825	0.829	0.824
	(0.077)	(0.084)	(0.076)
Wholesale Funding	0.189	0.198	0.187
	(0.125)	(0.109)	(0.128)
C&I Loans	0.104	0.111	0.102
	(0.072)	(0.073)	(0.071)
Tier 1 Ratio	0.146	0.149	0.145
	(0.085)	(0.104)	(0.080)
Cost of Funds	0.020	0.017	0.020
	(0.009)	(0.008)	(0.009)
Log No. Branches	1.391	1.839	1.288
	(1.108)	(1.446)	(0.986)
Obs.	47,783	8,958	38,825
	Whole Sample	Above-Median Liq. Exposure Counties	Below-Median Liq. Exposure Counties
	(1)	(2)	(3)
Panel D. County-Specific Shock (County-Year) & Small Business Dynamics (County-Industry-Year)			
Shale Liquidity Shock^{County}	1.033	1.951	0.115
	(1.910)	(2.366)	(0.105)
Obs.	29,459	14,729	14,730
Business Entry	0.101	0.101	0.101
	(0.182)	(0.182)	(0.182)
Jobs Created by Entry	0.076	0.074	0.077
	(0.180)	(0.174)	(0.185)
Incumbent Employment Growth	-0.038	-0.047	-0.029
	(2.068)	(2.844)	(0.683)
Business Exit	0.074	0.085	0.063
	(0.133)	(0.140)	(0.125)
Job Loss Due to Exit	0.062	0.070	0.054
	(0.136)	(0.142)	(0.130)
Obs.	1,662,604	831,452	831,152

Table 2: Shale Liquidity Shock and Bank Deposit Inflows

This table reports regression results of the effects of shale liquidity shocks on bank deposit growth at the bank-year level. The first column reports the first-stage regression result for the IV regressions, Columns 2, 4, 6, and 8 report the OLS results, and Columns 3, 5, 7, and 9 report the second-stage results using the IV regressions. The dependent variable is the annual growth rate of total deposits (Columns 2 and 3), retail deposits (Columns 4 and 5), time deposits of over $100,000 (Columns 6 and 7), and brokered deposits (Columns 8 and 9). Our key explanatory variable, *Shale liquidity shock*, is a bank-specific, time-varying measure on the degree of a bank's exposure to shale-induced liquidity gains. Specifically, $Shale\ liquidity\ shocks_{b,t} = \sum_j (Branches_{b,j,t} * Wells_{j,t} * Mktshr_{b,j,t}) / Branches_{b,t}$, where $Branches_{b,j,t}$ denotes the number of branches owned by bank b in county j in year t; $Branches_{b,t}$ denotes the total number of branches owned by bank b in year t; $Wells_{j,t}$ is the number of shale wells drilled in county j from 2003 as of year t; and $Mktshr_{b,j,t}$ equals the share of deposits in county j in year t that are held at bank b's branches in county j. Similarly, we construct the instrumental variable, *Shale liquidity shock preexisting branches*, using each bank's preexisting branch networks and market shares in 2002. We control for one-year-lagged bank characteristics including *Log assets*, *Equity ratio*, *Liquid assets*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, *Cost of funds*, *Log no. branches*, and *Charter type*, and bank and year fixed effects across all specifications. We estimate the model using either OLS or 2SLS (*Shale liquidity shock* is instrumented with *Shale liquidity shock preexisting branches*), with the standard errors two-way clustered at the bank and year level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	First Stage	Second Stage							
		Total Deposits Growth		Retail Deposits Growth		Time Deposits >$100k Growth		Brokered Deposits Growth	
		OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Shale liquidity shock preexisting branches	0.936***								
	(0.011)								
Shale liquidity shock		0.008***	0.009***	0.009**	0.012***	0.006**	0.009**	0.004	-0.001
		(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.017)	-0.022
Bank Char.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	47,783	47,783	47,783	47,783	47,783	47,783	47,783	47,783	47,783
R^2	0.95	0.19	0.19	0.15	0.15	0.20	0.20	0.17	0.17

Table 3: Bank Liquidity and SBA Loan Size

This table reports the 2SLS regression results of the effects of a bank's exposure to the shale liquidity shock on SBA loan size. We conduct the analyses at the loan level, focusing on borrowers located in non-shale counties only. The dependent variable is the log dollar amount of the originated SBA loans (*Loan size*). Our key explanatory variable is *Shale liquidity shock*, and its interaction with an indicator of whether a borrower is an established business at the time of loan origination (*Existing business*, Columns 2-3 where we differentiate borrowers the status of new/existing business), or indicators of a borrower's employee size (namely, *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, and *Employee* $\geq$ *10*, Columns 4-5 where we differentiate borrowers by employee size). *Shale liquidity shock* is a bank-specific, time-varying measure on the degree of a bank's exposure to shale-induced liquidity gains. *Bank Char.* represents an array of one-year-lagged bank-specific characteristics including *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, *Cost of funds*, *Log no. branches*, and *Charter type*. *Borrower Char.* denotes a set of borrower-specific traits at the time of loan origination, namely *Business organization*, *Employee size*, and/or *Existing business*. We estimate the model using 2SLS, where *Shale liquidity shock* (and its interaction with indicators of borrower type) are instrumented with *Shale liquidity shock preexisting branches* (and its interaction with corresponding indicators of borrower type), with the standard errors two-way clustered at the bank and year level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	SBA Loan Size				
		New vs. Existing Businesses		By Employee Size	
	(1)	(2)	(3)	(4)	(5)
Shale liquidity shock	0.040***	-0.019	-0.015	0.011	0.01
	(0.011)	(0.019)	(0.016)	(0.023)	(0.014)
Shale liquidity shock		0.090***	0.073***		
× Existing business		(0.019)	(0.021)		
Shale liquidity shock				0.019***	0.019**
× Employee ∈ [3,4]				(0.004)	(0.006)
Shale liquidity shock				0.038***	0.038***
× Employee ∈ [5,9]				(0.010)	(0.011)
Shale liquidity shock				0.056***	0.057***
× Employee ≥ 10				(0.014)	(0.015)
Borrower Char.			Y		Y
Bank Char.	Y		Y		Y
Bank-County-Ind-Type FE	Y	Y	Y	Y	Y
County-Ind-Year FE	Y	Y	Y	Y	Y
Obs.	473,433	473,433	473,433	473,433	473,433
R^2	0.62	0.60	0.64	0.65	0.66

Table 4: Bank Liquidity and SBA Interest Rate

This table reports the 2SLS regression results of the effects of a bank's exposure to the shale liquidity shock on SBA loan spread. We conduct the analyses at the loan level, focusing on borrowers located in non-shale counties. The dependent variable is the SBA loan interest rates in percentage points (*Interest rate*). Our key explanatory variable is *Shale liquidity shock*, and its interaction with an indicator of whether a borrower is an established business at the time of loan origination (*Existing business*, Columns 2-3 where we differentiate borrowers the status of new/existing business), or indicators of a borrower's employee size (namely, *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, and *Employee* $\geq$ *10*, Columns 4-5 where we differentiate borrowers by employee size). *Shale liquidity shock* is a bank-specific, time-varying measure on the degree of a bank's exposure to shale-induced liquidity gains. *Bank Char.* represents an array of one-year-lagged bank-specific characteristics including *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, *Cost of funds*, *Log no. branches*, and *Charter type*. *Borrower Char.* denotes borrower-specific traits at the time of loan origination, namely *Business organization*, *Employee size*, and *Existing business*. We estimate the model using 2SLS, where *Shale liquidity shock* (and its interaction with indicators of borrower type) are instrumented with *Shale liquidity shock preexisting branches* (and its interaction with corresponding indicators of borrower type), with the standard errors two-way clustered at the bank and year level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	SBA Interest Rate				
		New vs. Existing Businesses		By Employee Size	
	(1)	(2)	(3)	(4)	(5)
Shale liquidity shock	0.060	0.118	0.136	0.095	0.115
	(0.049)	(0.076)	(0.080)	(0.062)	(0.068)
Shale liquidity shock		-0.109*	-0.102*		
× Existing business		(0.052)	(0.053)		
Shale liquidity shock				-0.023	-0.022
× Employee $\in$ [3,4]				(0.014)	(0.014)
Shale liquidity shock				-0.063**	-0.062**
× Employee $\in$ [5,9]				(0.026)	(0.026)
Shale liquidity shock				-0.065**	-0.063***
× Employee $\geq$ 10				(0.020)	(0.019)
Borrower Char.			Y		Y
Bank Char.	Y		Y		Y
Bank-County-Ind-Type FE	Y	Y	Y	Y	Y
County-Ind-Year FE	Y	Y	Y	Y	Y
Obs.	473,433	473,433	473,433	473,433	473,433
R^2	0.62	0.63	0.63	0.65	0.65

Table 5: Bank Liquidity and CRA Small Business Lending

This table reports the 2SLS regression results of the effects of a bank's exposure to the shale liquidity shock on small business lending from the CRA data. We conduct the analyses at the bank-county-year level. The dependent variable is the log dollar amount of annual CRA lending (*Total loan amount*) by each bank to each county in columns with the odd number, and the log total number of CRA lending (*Total loan number*) in columns with the even number. Columns 1 and 2 use the aggregate amount of small business loans with loan size no larger than $100,000; Columns 3 and 4 use the aggregate amount of small business loans with loan size between $100,000 and $250,000; Columns 5 and 6 use the aggregate amount of small business loans with loan size above $250,000. Our key explanatory variable, *Shale liquidity shock*, is a bank-specific, time-varying measure on the degree of a bank's exposure to shale-induced liquidity gains. *Bank Char.* represents an array of one-year-lagged bank-specific characteristics including *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, *Cost of funds*, *Log no. branches*, and *Charter type*. We include bank-county and county-year fixed effects in all specifications. We estimate the model using 2SLS, where *Shale liquidity shock* is instrumented with *Shale liquidity shock preexisting branches*, with the standard errors two-way clustered at the bank and year level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Loan size $\leq$ \$100*k*		*Loan size* $\in$ (\$100*k*, \$250*k*)		*Loan size* $\in$ (\$250*k*, \$1*m*)	
	Amount	Number	Amount	Number	Amount	Number
	(1)	(2)	(3)	(4)	(5)	(6)
Shale liquidity shock	-0.006	-0.008	0.020	0.005	0.072***	0.016***
	(0.028)	(0.027)	(0.018)	(0.005)	-0.02	-0.005
Bank Char.	Y	Y	Y	Y	Y	Y
Bank-County FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y
Obs.	725,745	725,745	725,745	725,745	725,745	725,745
R^2	0.81	0.89	0.77	0.88	0.78	0.88

Table 6: County Liquidity Shock and Small Business Entry

This table reports the 2SLS regression results of the effects of county-specific liquidity shocks on the creation of small businesses in non-shale counties. According to the U.S. Census, we focus on businesses with the number of employees below 100. The unit of analysis is county-industry(two-digit SIC)-year in Columns 1 and 4, and county-industry-type-year in Columns 2, 3, 5, and 6, where *type* refers to indicators of establishments' employee size group (namely, *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, and *Employee* $\geq$ *10*). The dependent variable in Columns 1-3 is *Business entry*, defined as the number of small establishment openings scaled by the number of small establishments at the beginning of the year. The dependent variable in Columns 4-6 is *Jobs created by entry*, defined equal to the number of new jobs created from establishment openings, scaled by the total number of jobs provided by small establishments at the beginning of the year. The explanatory variable, *Shale liquidity shock*^{County}, is a time-varying, county-specific measure of the degree to which banks in a non-shale county receive shale liquidity shocks through their branch networks in shale counties. *County Char.* represents a set of one-year-lagged county-specific characteristics (*Log population*, *Log income per capita*, *Labor market participation*, *Proprietorship*, *Log No. local branches*, and *Small business lending HHI*), and *Avg. Bank Char.* denotes the weighted average one-year-lagged bank characteristics in each county (i.e., *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, and *Cost of funds*). Appendix Table A1 provides detailed variable definitions. We estimate the model using 2SLS, where *Shale liquidity shock*^{County} (and its interaction with indicators of borrowers' employee size) are instrumented with *Shale liquidity shock preexisting branches*^{County} (and its interaction with indicators of borrowers' employee size), with the standard errors two-way clustered at the county and year level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Business Entry			Jobs Created by Entry		
	(1)	(2)	(3)	(4)	(5)	(6)
Shale liquidity shock^{County}	0.0004	-0.003	-0.003	-0.0004	0.000	0.000
	(0.0006)	(0.005)	(0.005)	(0.0005)	(0.006)	(0.006)
Shale liquidity shock^{County}		0.002	0.002		-0.004	-0.004
× Employee $\in$ [3,4]		(0.006)	(0.006)		(0.006)	(0.006)
Shale liquidity shock^{County}		0.004	0.004		-0.001	-0.001
× Employee $\in$ [5,9]		(0.007)	(0.008)		(0.009)	(0.009)
Shale liquidity shock^{County}		0.004	0.004		0.001	0.001
× Employee $\geq$ 10		(0.009)	(0.009)		(0.011)	(0.011)
County Char.	Y		Y	Y		Y
Avg. Bank Char.	Y		Y	Y		Y
County-Ind FE	Y			Y		
County-Ind-Type FE		Y	Y		Y	Y
Ind-Year FE	Y	Y	Y	Y	Y	Y
Obs.	1,662,604	4,774,173	4,774,173	4,774,173	4,774,173	4,774,173
R^2	0.34	0.30	0.30	0.30	0.28	0.28

Table 7: County Liquidity Shock and Small Business Expansion

This table reports the 2SLS regression results of the effects of county-specific liquidity shocks on the employment growth for the incumbent businesses in non-shale counties. According to the U.S. Census, we focus on businesses with the number of employees below 100. The unit of analysis is county-industry(two-digit SIC)-year in Column 1, and county-industry-type-year in Columns 2 and 3, where *type* refers to indicators of establishments' employee size group (namely, *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, and *Employee* $\geq$ *10*). The dependent variable, *Incumbent employment growth*, is the annual growth rate of employees for the incumbent firms. The explanatory variable, *Shale liquidity shock^{County}*, is a time-varying, county-specific measure of the degree to which banks in a non-shale county receive shale liquidity shocks through their branch networks in shale counties. *County Char.* represents a set of one-year-lagged county-specific characteristics (*Log population*, *Log income per capita*, *Labor market participation*, *Proprietorship*, *Log No. local branches*, and *Small business lending HHI*), and *Avg. Bank Char.* denotes the weighted average one-year-lagged bank characteristics in each county (i.e., *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, and *Cost of funds*). Appendix Table A1 provides detailed variable definitions. We estimate the model using 2SLS, where *Shale liquidity shock^{County}* (and its interaction with indicators of borrowers' employee size) are instrumented with *Shale liquidity shock preexisting branches^{County}* (and its interaction with indicators of borrowers' employee size), with the standard errors two-way clustered at the county and year level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Incumbent Employment Growth		
	(1)	(2)	(3)
Shale liquidity shock^{County}	-0.0001	-0.009***	-0.009***
	(0.0007)	(0.003)	(0.003)
Shale liquidity shock^{County}		0.013***	0.012***
× Employee $\in$ [3,4]		(0.003)	(0.003)
Shale liquidity shock^{County}		0.013***	0.012***
× Employee $\in$ [5,9]		(0.003)	(0.003)
Shale liquidity shock^{County}		0.017***	0.017***
× Employee $\geq$ 10		(0.004)	(0.004)
County Char.	Y		Y
Avg. Bank Char.	Y		Y
County-Ind FE	Y		
County-Ind-Type FE		Y	Y
Ind-Year FE	Y	Y	Y
Obs.	1,662,604	4,760,639	4,760,639
R^2	0.10	0.11	0.12

Table 8: County Liquidity Shock and Small Business Exit

This table reports the 2SLS regression results of the effects of county-specific liquidity shocks on the exit of small businesses in non-shale counties. According to the U.S. Census, we focus on businesses with the number of employees below 100. The unit of analysis is county-industry(two-digit SIC)-year in Columns 1 and 4, and county-industry-type-year in Columns 2, 3, 5, and 6, where *type* refers to indicators of establishments' employee size group (namely, *Employee* $\in$ *[3,4]*, *Employee* $\in$ *[5,9]*, and *Employee* $\geq$ *10*). The dependent variable in Columns 1-3 is *Business exit*, defined as the number of small establishment closings scaled by the number of small establishments at the beginning of the year. The dependent variable in Columns 4-6 is *Jobs loss due to exit*, defined as the number of jobs destroyed by establishment closings scaled by the total number of jobs offered by small establishments at the beginning of the year. The explanatory variable, *Shale liquidity shock^{County}*, is a time-varying, county-specific measure of the degree to which banks in a non-shale county receive shale liquidity shocks through their branch networks in shale counties. *County Char.* represents a set of one-year-lagged county-specific characteristics (*Log population*, *Log income per capita*, *Labor market participation*, *Proprietorship*, *Log No. local branches*, and *Small business lending HHI*), and *Avg. Bank Char.* denotes the weighted average one-year-lagged bank characteristics in each county (i.e., *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, and *Cost of funds*). Appendix Table A1 provides detailed variable definitions. We estimate the model using 2SLS, where *Shale liquidity shock^{County}* (and its interaction with indicators of borrowers' employee size) are instrumented with *Shale liquidity shock preexisting branches^{County}* (and its interaction with indicators of borrowers' employee size), with the standard errors two-way clustered at the county and year level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Business Exit			Job Loss Due to Exit		
	(1)	(2)	(3)	(4)	(5)	(6)
Shale liquidity shock^{County}	0.0007	0.006***	0.006***	0.0008*	0.006***	0.006***
	(0.0004)	(0.0020)	(0.002)	(0.0004)	(0.002)	(0.0020)
Shale liquidity shock^{County}		-0.009**	-0.008**		-0.008**	-0.008**
× Employee $\in$ [3,4]		(0.003)	(0.003)		(0.003)	(0.003)
Shale liquidity shock^{County}		-0.007**	-0.007**		-0.007**	-0.006**
× Employee $\in$ [5,9]		(0.003)	(0.003)		(0.003)	(0.003)
Shale liquidity shock^{County}		-0.009**	-0.009**		-0.009**	-0.008**
× Employee $\geq$ 10		(0.003)	(0.003)		(0.003)	(0.003)
County Char.	Y		Y	Y		Y
Avg. Bank Char.	Y		Y	Y		Y
County-Ind FE	Y			Y		
County-Ind-Type FE		Y	Y		Y	Y
Ind-Year FE	Y	Y	Y	Y	Y	Y
Obs.	1,662,604	4,760,639	4,760,639	4,760,639	4,760,639	4,760,639
R^2	0.27	0.24	0.24	0.24	0.23	0.23

Table 9: County Liquidity Shock and Small Business Dynamics, Differentiate by EFD

This table reports the 2SLS regression results of the effects of county-specific liquidity shocks on small business dynamics that are similar to Table 7 & 8, while differentiating businesses by their external finance dependence (EFD) that is constructed in a similar way to Rajan and Zingales (1998). Columns 1, 3, and 5 use a subsample of establishments with bottom-quartile EFD, while Columns 2, 4, and 6 use a subsample of establishments with top-quartile EFD. The unit of analysis is county-industry-type-year in all columns, where *type* refers to indicators of establishments' employee size group (namely, *Employee* $\in [3,4]$, *Employee* $\in [5,9]$, and *Employee* ≥ 10). The dependent variable is *Incumbent employment growth*, *Business exit*, and *Job loss due to exit* in Columns 1-2, 3-4, and 5-6, respectively. The explanatory variable, *Shale liquidity shock*^{County}, is a time-varying, county-specific measure of the degree to which banks in a non-shale county receive shale liquidity shocks through their branch networks in shale counties. *County Char.* represents a set of one-year-lagged county-specific characteristics (*Log population*, *Log income per capita*, *Labor market participation*, *Proprietorship*, *Log No. local branches*, and *Small business lending HHI*), and *Avg. Bank Char.* denotes the weighted average one-year-lagged bank characteristics in each county (i.e., *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, and *Cost of funds*). Appendix Table A1 provides detailed variable definitions. We estimate the model using 2SLS, where *Shale liquidity shock*^{County} and its interaction with indicators of borrowers' employee size are instrumented with *Shale liquidity shock preexisting branches*^{County} and its interaction with indicators of borrowers' employee size, with the standard errors two-way clustered at the county and year level and reported in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Incumbent Employment Growth		Business Exit		Job Loss Due to Exit	
	(1)	(2)	(3)	(4)	(5)	(6)
	EFD: Q1	EFD: Q4	EFD: Q1	EFD: Q4	EFD: Q1	EFD: Q4
Shale liquidity shock^{County}	-0.005**	-0.009***	0.004**	0.007***	0.004**	0.008***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Shale liquidity shock^{County}	0.007*	0.014***	-0.006	-0.012***	-0.005	-0.013***
× Employee $\in$ [3,4]	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Shale liquidity shock^{County}	0.004*	0.012***	-0.002	-0.008**	-0.002	-0.009***
× Employee $\in$ [5,9]	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Shale liquidity shock^{County}	0.007**	0.017***	-0.004	-0.010***	-0.004	-0.010***
× Employee $\geq$ 10	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
County Char.	Y	Y	Y	Y	Y	Y
Avg. Bank Char.	Y	Y	Y	Y	Y	Y
County-Ind-Type FE	Y	Y	Y	Y	Y	Y
Ind-Year FE	Y	Y	Y	Y	Y	Y
Obs.	1,115,973	1,132,921	1,115,973	1,132,921	1,115,973	1,132,921
R^2	0.12	0.16	0.23	0.24	0.23	0.23

Appendix

Table A1 Variable Definition

Variable	Definition
SBA Loan-Level Variables	
Loan Outcomes	
Loan size	Log dollar amount of an SBA loan. Source: SBA 7(a) loans
Interest rate	The interest rate in percentage points. Source: SBA 7(a) loans
Borrower Types	
Existing business	An indicator equal to one if a borrower has already established its business at the time of loan origination, and zero otherwise. Source: SBA 7(a) loans
Employee $\in$ *[3,4]*	An indicator equal to one if a borrower has 3-4 employees, and zero otherwise. Source: SBA 7(a) loans
Employee $\in$ *[5,9]*	An indicator equal to one if a borrower has 5-9 employees, and zero otherwise. Source: SBA 7(a) loans
Employee $\geq$ *10*	An indicator equal to one if a borrower has 10 or more employees, and zero otherwise. Source: SBA 7(a) loans
Borrower Characteristics	
Business organization	A set of dummy variables equal to one if a business is a proprietorship, partnership, or corporation. Source: SBA 7(a) loans
CRA Small Business Lending	
Total loan amount	Log dollar amount of small business loans originated by each bank to each county. CRA further breaks down the lending volume into three loan-size categories: $100,000 or less, between $100,000 and $250,000, and more than $250,000 (and below $1 million). Source: CRA data
Total loan number	Log number of small business loans originated by each bank to each county. CRA further breaks down the lending volume into three loan-size categories: $100,000 or less, between $100,000 and $250,000, and more than $250,000 (and below $1 million). Source: CRA data
Small Business Dynamics	
Business entry	The number of new establishment openings in a year adjusted by the number of existing establishments at the beginning of the year. Source: NETS database

Jobs created by entry	The number of new jobs created from establishment openings scaled by the total number of jobs provided by small establishments at the beginning of the year. Source: NETS database
Incumbent employment growth	The annual employment growth of the incumbent establishments. Source: NETS database
Business exit	The number of establishment closings in a year scaled by the number of establishments at the beginning of the year. Source: NETS database
Job loss due to exit	The number of jobs destroyed by establishment closings scaled by the total number of jobs offered by small establishments at the beginning of the year. Source: NETS database
Bank-Specific Liquidity Shock Measure	
Shale liquidity shock	A time-varying, bank-specific liquidity shock measure that equals the share of a bank's branches that are located in shale counties, weighted the number of branches in each shale county by the intensity of liquidity gains received by the bank in the county. Formally, $$Shale\ liquidity\ shock_{b,t} = \sum_j \left(Branches_{b,j,t} * Wells_{j,t} * Mktshr_{b,j,t}\right) / Branches_{b,t}, \quad (1)$$ where b, j, and t represent bank, county, and year, respectively. $Branches_{b,j,t}$ denotes the number of branches owned by bank b in county j in year t; $Branches_{b,t}$ denotes the total number of branches owned by bank b in year t; $Wells_{j,t}$ is the number of shale wells drilled in county j from 2003 as of year t; and $Mktshr_{b,j,t}$ equals the share of deposits in county j in year t that are held at bank b's branches in county j. Source: IHS Markit Energy, FDIC's Summary of Deposits
Shale liquidity shock preexisting branches	The instrument for bank-specific *Shale liquidity shock*, using each bank's preexisting branch structure back in 2002. Specifically, $$Shale\ liquidity\ shock\ preexisting\ branches_{b,t} = \sum_j \left(Branches_{b,j,2002} * Wells_{j,t} * Mktshr_{b,j,2002}\right) / Branches_{b,2002}, \quad (2)$$ where b, j, t, and $Wells_{j,t}$ are defined the same as in Equation (1) above. $Branches_{b,j,2002}$ denotes the number of branches owned by bank b in county j in 2002; $Branches_{b,2002}$ denotes the total number of branches owned by bank b in 2002; and $Mktshr_{b,j,2002}$ equals the share of total deposits in county j in year 2002 that are held by bank b in county j. Source: IHS Markit Energy, FDIC's Summary of Deposits
County-Specific Liquidity Shock Measure	

Shale liquidity shock^{County}	A time-varying, county-specific measure of the degree to which banks in each county receive liquidity shocks through their branch networks in shale counties. Specifically, $Shale\ liquidity\ shock^{County}{}_{j,t} = \sum \omega_{b,j,t} * Shale\ Liquidity\ shock_{b,t}$. (6) *Shale liquidity shock*$^{County}{}_{j,t}$ denotes the extent to which banks in county j receive shale liquidity shocks in year t. $\omega_{b,j,t}$ equals the amount of small business lending originated by bank b in county j in year t, as a share of the total amount of small business lending across all banks in county j in year t based on the CRA data; *Shale liquidity shock*$_{b,t}$ is the same bank-specific liquidity shock measure defined in Equation (1).
Shale liquidity shock preexisting branches^{County}	The instrument for county-specific *Shale liquidity shock*^{County}, using each bank's preexisting branch structure, and small business lending volume back in 2002. Specifically, $Shale\ liquidity\ shock\ preexisting\ branches^{County}{}_{j,t} = \sum \omega_{b,j,2002} * Shale\ Liquidity\ shock\ preexisting\ branches_{b,t}$, (7) where *Shale liquidity shock preexisting branches*$^{County}{}_{j,t}$ denotes the extent to which banks in county j receive shale liquidity shocks in year t based on preexisting bank branch networks back in 2002; $\omega_{b,j,2002}$ is the share of small business lending originated by bank b in county j in 2002 based on the CRA data; And *Shale liquidity shock preexisting branches*$_{b,t}$ is the same bank-specific liquidity shock measure based on each bank's preexisting branches defined in Equation (2).
Bank Characteristics	
Total deposits growth	The annual growth rate of total deposits. Source: Call Report
Time deposits >$100k growth	The annual growth rate of time deposits of $100,000 or more. Source: Call Report
Brokered deposits growth	The annual growth rate of brokered deposits. Brokered deposits refer to those deposits accepted by a bank from or through the mediation or assistance of a third party, such as a person or company or organization other than the owner of the deposit. Source: Call Report
Retail deposits growth	The annual growth rate of retail deposits. Retail deposits equals total deposits excluding time deposits of $100,000 or more and brokered deposits. Source: Call Report
Log assets	Log of total assets. Source: Call Report
Equity ratio	Total equity divided by total assets. Source: Call Report

Liquid assets	Cash plus marketable securities divided by total assets. Source: Call Report
Deposits	Total deposits divided by total assets. Source: Call Report
Wholesale funding	Large-denomination certificates of deposits, brokered deposits, and federal funds purchased and securities sold under repurchase agreements divided by total assets. Source: Call Report
C&I loans	Commercial and industrial loans divided by total assets. Source: Call Report
Tier 1 ratio	Tier 1 capital divided by total risk-weighted assets. Source: Call Report
Cost of funds	Total interest expenses divided by interest-bearing liabilities. Source: Call Report
Log No. branches	Log of total number of branches owned by a bank. Source: Summary of Deposits
Charter type	An indicator that equals one if a bank is national charted, and zero if state charted. Source: Call Report
County Characteristics	
Log population	Log of total population in each county in a year. Source: Bureau of Economic Analysis
Log income per capita	Log of total personal income of a county divided by the resident population of the county. Source: Bureau of Economic Analysis
Labor market participation	The number of persons aged 16 and older divided by the total population. Source: Bureau of Labor Statistics
Proprietorship	The share of employment that is sole proprietorships or general partnership. Source: Bureau of Economic Analysis
Log No. local branches	Log of the total number of bank branches in each county in a year. Source: Summary of Deposits
Small business lending HHI	The Herfindahl-Hirschman index (HHI) of small business lending amount in each county in a year. Source: CRA data
Average bank characteristics	A set of county-specific bank characteristics (including *Log assets*, *Equity ratio*, *Liquid assets*, *Deposits*, *Wholesale funding*, *C&I loans*, and *Tier 1 ratio*, averaged at the county level). Take *Log assets* as an illustrative example, we calculate the county-specific *Log assets* as the weighted average of bank-specific *Log assets* across banks in each county, weighted each bank by its share of small business lending in that particular county. Using the same approach, we construct county-specific bank characteristics for each of the bank traits. Source: Call Report; CRA data