Bank Liquidity, Small Business Lending, and Real Outcomes

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Abstract

Combining a novel and detailed SBA loan-level database with time-varying, bank-specific liquidity shocks, we evaluate the effects of bank liquidity conditions on small business lending and subsequent job and business creations, while differentiating borrowers by size and age. To establish causality, we construct time-varying, bank-specific liquidity shock measures that exploit exogenous liquidity windfalls to local bank branches resulting from the shale development activities since 2003. Our results suggest that positive liquidity shocks enhance bank lending only to relatively large and established small businesses, not to very small and young ones. Moreover, using comprehensive establishment dynamic data from the National Establishment Time-Series (NETS), we show that positive liquidity shocks facilitate jobs created by relatively large small business and lower their exit rates. Our results are not driven by changes in local economic conditions due to the shale boom, as we exclude borrowers located in counties with any shale development. Our findings suggest that banks are adequate to promote access to finance for certain types of small business borrowers, but not necessarily for all.

JEL: G21, G28, G30, E24, Q40

Keywords: Banks, Small business lending, Business creation, Employment

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I. Introduction

As a key driving engine of economic growth and job creation, small businesses in the U.S., according to the Small Business Administration (SBA), produced 45% of the private nonfarm GDP in 2010 and accounted for 63% of net new jobs from 1992 to 2013 (see also, Berger, Bouwman, and Kim, 2017). Although bank credit is generally considered the most important source of external finance for small businesses (Petersen and Rajan, 1994; Berger, Saunders, Scalise, and Udell, 1998; Berger and Udell, 1998), it remains unclear how changes in the liquidity conditions of the banking system affect small business lending, with subsequent implications on business creation, growth, and employment. What seems to puzzle the policy makers is that despite the massive liquidity injection to the banking sector over the economic recovery period since the 2007-08 financial crisis, small-business access to finance remains tough in the U.S.: From 2011 to 2014, the share of commercial and industrial (C&I) loans to small businesses has dropped from 25% to 21% (estimated from the Call reports), with the approval rate of loan application shrinking from 62% to 58% among small business applicants.[1]

These observations challenge the conventional wisdom on the role of traditional banking in facilitating small businesses. Are commercial banks the most appropriate credit providers for these growth drivers? To what extent would liquidity shocks to the banking system translate into lending to small businesses, especially to those youngest and smallest enterprises? More specifically, in this study, we evaluate the impact of banks' liquidity conditions on lending to different types of small businesses, and, corresponding real outcomes of the creation and destruction of businesses, as well as employment.

Existing research provides valuable insights on the rationale of expecting heterogeneous lending outcomes for different types of small businesses. First, as traditional financial intermediaries, banks tend to make credit decisions based on borrowers' hard information, such as

[1] 2011 Small Business Finances Poll and 2014 Joint Small Business Credit Survey Report by the Federal Reserve Bank of New York.

historical financial statements and quantitative performance (Petersen and Rajan, 1994; Berger and Udell, 1995). Among small businesses, there are nontrivial variations of information asymmetries between these firms and potential lenders. Due to a lack of track records, smallest and youngest firms tend to face tightening financial constraints, as it is hard for a potential lender to evaluate their quality and creditworthiness. Second, researchers have shown that the credit rationing problem is more severe among smaller firms, as they tend to be poorly capitalized (Kashyap, Stein, and Wilcox, 1993; Kashyap and Stein, 1994; Gertler and Gilchrist, 1994). Along this line, we expect that an improvement in banks liquidity conditions might be particularly beneficial to businesses that have achieved a certain level of size with enough skin in game. Third, prior research also suggests that banks can facilitate small firms' access to finance through relationship lending (Sharpe 1990; Boot, 2000; Boot and Thakor, 2000; Agarwal and Hauswald, 2010; Berger, Bouwman, and Kim, 2017). Establishing lending-borrowing relationship enables banks to gather soft information, such as the skill and character of a small business owner, which is unlikely to be revealed through financial statements or rating agencies. In our context, the liquidity inflows received by banks should benefit their relationship borrowers (existing businesses) more than new customers (the young startups). Taken together, we expect bank lending to smallest and youngest firms to be much less responsive to changes in bank liquidity conditions than that of relatively large and established ones.

To shed light on these questions, we first exploit a unique and rich dataset that contains detailed loan-level information for small business loans through SBA 7(a) lending programs. The data provides the identity of the lender and the borrower, their geographic locations, as well as specific loan terms including amount, interest rate, and maturity. Importantly, the dataset enables us to differentiate borrowers by size and availability of past performance, so that we could assess the potential heterogeneous effects on loans to small businesses that fall into different categories. Moreover, we use the National Establishment Time-Series (NETS) database that offers comprehensive information on employment, geographic location, industry, and operating years for the universe of U.S. establishments. We use this second database to evaluate the real impact of positive liquidity shocks on small business creation, expansion, and destruction.

To assess the impact of banks' liquidity conditions on small business lending outcomes, we employ an identification strategy that exploits exogenous liquidity windfalls for local bank branches resulting from the shale development activities. More specifically, an unexpected technological breakthrough that facilitates shale development took the energy sector by surprise in 2003. The technological advancements in fracking enable the oil and gas companies to extract shale resources in an economically profitable way, making shale gas the primary source of natural gas production in the U.S. The shale development activities require oil and gas companies to purchase mineral leases from local property owners in promising areas. The mineral leases typically involve a large upfront bonus based on the number of leased acres plus a royalty percentage on the production from the lease. In our context, landowners who receive large leasing payments deposit into nearby bank branches, creating a positive liquidity shock for individual banks. We provide empirical evidence that validates our empirical setup: Deposits of banks that are exposed to shale liquidity shocks are shown to grow faster by about 1.36 percentage points than those of banks that do not receive the shock.

Using a comprehensive well database purchased from *IHS Markit Energy* together with the publicly available bank branch data of *Summary of Deposit*, we construct a time-varying, bank-specific measure on the extent to which each bank is exposed to shale liquidity shocks via its branch networks. Our primary measure of *Shale liquidity shock* equals the proportion of branches that are located in counties with shale development, where the number of branches in each county is weighted by the intensity of liquidity windfalls received by that bank in that particular county.

We treat shale-induced liquidity inflows as exogenous shocks to individual banks for at least two reasons. First, the technological improvements in fracking are unexpected, since not even the oil and gas industry anticipated the advent of the subsequent shale development activities across the nation. Second, it is very unlikely for banks to adjust their branch networks in order to gain greater exposure to shale liquidity shocks, because (a) it is difficult, even for the energy companies, to predict shale discoveries in different geographies, and (b) the process of purchasing mineral leases often occurs very rapidly. Nevertheless, we construct an instrument for our bank-level liquidity shock measure, using each bank's branch networks in 2002, before the onset of large scale shale development. Our first-stage regression from the 2SLS tests suggest an F-statistic of 340, easily passing the relevance test threshold. As banks could not possibly have expected the technological breakthroughs in fracking back in 2002, this instrument satisfies the exclusion restriction.

We report and discuss our empirical results in three folds, (1) SBA loan-level outcomes, (2) the aggregate amount of small business lending, and (3) the ultimate real outcomes on business creation, employment growth, and exit. First, using the SBA loan-level data, we find sharp contrasting effects on borrowing establishments with small vs. relatively large size and those with new vs. existing business. Specifically, banks exposed to shale liquidity shocks originate SBA loans with an average larger size and more favorable loan terms (lower interest rates or longer maturities) than banks without such exposure. Perhaps more importantly, these credit-enhancing effects are significant only for relatively larger or more established borrowing businesses, but not for those very small businesses or completely new startups. The economic difference between different borrowing groups is large. Our most conservative coefficients suggest that banks that receive an average shale liquidity shock (1.7) would increase the average loan size to existing businesses (relatively larger borrowers) by 11% (7%) more than to those newly established (very small) ones.

Second, we find that the impact of shale-induced liquidity shocks on the county-specific, aggregate amount of small business lending varies across business types and loan size. We obtain consistent results using two complementary data sources: the aggregated amount of SBA loans allow us to differentiate borrowers by business type, whereas the aggregate amount of small business lending provided by Community Reinvestment Act (CRA) database represents the vast majority small business lending by U.S. commercial banks in each county. We show that the effects of banks liquidity shocks on aggregate SBA loan volumes are pronounced only among borrowers with an established existing business or those with a relatively large size. Specifically, banks with positive liquidity shocks are shown to increase only large dollar loans to small business – defined as loans with a size above $250,000 using CRA data. This suggests that majority small businesses cannot benefit from banks' liquidity shocks, since 70% of small business seek loans in amounts under $250,000 (Mills and McCarthy, 2016). Crucially, we remove counties with shale development from our analyses, and thus focus only on those specially those without any shale wells drilled, mitigating the concern that the credit-enhancing effects are driven by changes in local demand due to the shale development activities rather than the expansion of credit supply.

Furthermore, we use comprehensive establishment dynamic NETS data that covers the universe of U.S. establishments, to evaluate the subsequent effects on creation and destruction of small business creation, and jobs created by small businesses. Our analyses suggest that shale liquidity shocks that facilitate small business lending ultimately translate into real outcomes on the creation of small establishments, employment growth, and business exit, and, the effects of liquidity shocks on the dynamics of small businesses vary across business size. We find that (a) the number of small firms in a county increases with shale liquidity shocks, but only among those firms with employee size above a certain threshold; (b) employment grow faster by 22% of the sample average value among relatively-large businesses in a county that receives an average liquidity shock; and (c) relatively large businesses also exit at a lower rate in counties that are exposed to the positive liquidity shocks than counties without the exposure.

To our knowledge, this is the first study that evaluates the differential effects of bank liquidity conditions on small and medium enterprise (SME) lending. Exploiting detailed loan-level and area-specific data together with time-varying, bank-specific liquidity shocks, our study provides novel evidence showing that bank loans to small and young firms are much less responsive to an improvement in bank liquidity conditions than those to relatively large and well established small businesses. Building on prior research that highlights the essential role of banks in alleviating small business financial constraints via lending relationship (Sharpe 1990; Boot and Thakor, 2000; Canales and Nanda, 2012; Berger, Bouwman, and Kim, 2017), our analyses suggest that banks are adequate to promote access to finance for some types of small business borrowers, but not necessarily for all.

Moreover, by linking effects of credit provisions to SME with subsequent real outcomes on the creation of small businesses and jobs, our work also relates to a rapidly growing body of literature that examines credit supply to businesses and its real economic impact (Brown, Cookson, and Heimer, 2017; Brown and Earle, 2017; Butler and Cornaggia, 2011; Kerr and Nanda, 2009; Krishnan, Nandy, and Puri, 2015).

The rest of the paper proceeds as follows. Section II describes data source and variable definitions. Section III describes our identification strategy, provides institutional backgrounds on technological breakthroughs in fracking that facilitates the shale development activities, and constructs a bank-specific liquidity shock. Section IV discusses the empirical results of the impact of shale liquidity shocks on small business lending, and real outcomes on the creation and destruction of small businesses and jobs. And Section V concludes.

II. Data and Sample

We employ data from a variety sources to evaluate the impact of shale liquidity shocks on small business lending, and subsequent area-specific, small-business related economic outcomes. Specifically, we use information on (a) the specific small business loan contract terms, including loan size, spreads, and maturities, (b) the amount of small business lending to each county provided by a bank in a given year, (c) the creation, expansion, and destruction of small establishments.

2.1 SBA loans

We obtain contract-level data from the 7(a) loan programs administered by the U.S. Small Business Administration (SBA), an independent agency of the federal government that provides services and assistance to small businesses to achieve the primary goal of growing (small) businesses and creating jobs.

We use a confidential version of the SBA 7(a) loan data over the period of 2003 – 2012, which includes 683,272 loans to eligible small businesses with a total amount of $137 billion. The SBA sample is well suited for our purposes, as only firms below certain employee thresholds or sales thresholds are qualified for the loan programs. For each loan contract, our data contains information on the date of approval, the identity and location of both the lender and the borrower, loan amount, maturity, and interest rate. To address the concern that local demand for small business loans might shift in the wake of shale development, we exclude loans with borrowing businesses located in counties with any shale development since 2003, and thus focus on a sample of borrowers located in "non-shale" counties only.

To obtain each lender's exposure to the shale liquidity shock, we manually link lenders in SBA 7(a) database with the banking institutions in FDIC's Summary of Deposits (SOD) data. We first conduct a fuzzy match based on a lender's name, street address, city, state and zip code. We then perform a manual check on all the matches to ensure accuracy. In this way, we successfully link 2,632 distinct lenders for 439,272 SBA loans, which accounts for 64% of the entire 7(a) loan records since 2003.

Our loan-level analyses examine the impact of lender liquidity shocks on three quantitative measures of loan terms: namely the logarithm of the loan amount (*Loan amount*), the level of interest rate at the time of loan approval (*Interest rate*), and the length of loan term measured in the number of month (*Maturity*). Table 1 Panel A shows that the average loan amount in our SBA loan sample is $225,000, the average interest rate equals to 7.6%, and the average loan maturity is 8.5 years. SBA 7(a) loan database allows us to control for a set of borrower-specific characteristics, including indicators of *Business organization* (proprietorship, partnership, or corporation), *Employee size* (the number of employees for each borrowing business)[2], and an indicator of *Existing business* that equals to one if a business already exists at the time of the loan origination, and zero otherwise.

2.2 CRA small business lending

We also use Community Reinvestment Act (CRA) database provided by the Federal Financial Institutions Examination Council (FFIEC) to retrieve information on small business credit at the bank-county-year level. All banking institutions that meet certain asset size thresholds are required to report, on an annual basis, the aggregate number and amount of small business loans for each geographic area in which it originated a loan. Small business loans are defined as those with original amounts $1million or less and were reported on the institution's regulatory financial reports as either "Loans secured by nonfarm or nonresidential real estate" or "Commercial and industrial loans". Thus, CRA data provides comprehensive information on the small business lending pattern of each bank for each county over a year.

We compile a sample of more than 900,000 observations on small business loans at the bank-county-year level during the sample period of 2003 – 2014. Our sample starts from 2003 because this is the first year of the technological advancement that facilitates the shale development. Accordingly, for each bank *b* during year *t*, we consider the volume ($\textit{Total loan amount}_{b,j,t}$) and number ($\textit{Total loan number}_{b,j,t}$) of small business loans made to a particular U.S. county *j*. As the aggregate number and volume of loans to small businesses are reported based on the origination amounts, we further measure *Total loan amount* and *Total loan number* within each of the three categories recorded in CRA database: $100,000 or less, between $100,000 and $250,000, and more than $250,000. The breakdown of small business lending by loan size allows us to investigate the impact of bank liquidity shocks on small business loans that fall into different size categories.

[2] *Employee size* represents a set of dummy variables indicating size 1, 2, 3, 4, 5-9, 10-19, and 20 and above.

As shown in Table 1 Panel B column (1), the aggregate CRA lending amounts to about $3 million for an average bank-county pair, which involves 71 loans with an average size of $108,000 dollars. Panel B also reports the summary statistics for two separate groups based on whether a bank receives a positive liquidity shock or not. As shown in columns (2) and (3), while banks exposed to shale liquidity shocks on average originate a smaller number of loans, the average loan size (and the total lending amount) is about 1.6 (and twice) as large as that of banks that did not receive a liquidity shock.

2.3 National Establishment Time-Series (NETS) database

We next evaluate whether bank liquidity shocks that facilitates small business lending have a subsequent real impact on (a) the creation of small businesses, (b) jobs created by small businesses, and (c) business exit. To do this, we utilize the 2014 National Establishment Time-Series (NETS) database, which provides longitudinal information for over 58.8 million establishments. The NETS database is a unique establishment-level database that covers the universe of U.S. businesses, and provides comprehensive information on employment, geographic location, industry, and operating years at the establishment level. With the NETS data, we can assess the effects on small business creation, expansion, and exit, and more importantly, in which region and business size.

To measure small business creation, for each county and industry group in a year, we calculate (1) *Small business creation* as the logarithm of the total number of establishments with employees below 50; (2) *Employment growth* as the log change of employment between period t and $t+1$ for businesses that already exist at time t; and (3) *Small business exit* that equals the proportion of establishments closed. We further break down these measures by employment size (whether the number of employees is above or below 5), which enables us to examine the potential different effects of liquidity shocks on the net creation of small businesses of different size categories. Table 1 Panel D provides the summary statistics of these NETS establishment measures.

2.4 Bank- and county-level characteristics

Our analyses controls for an array of bank traits, constructed from the Reports of Condition and Income ("Call Reports") that provide financial statements for each banking institution. We include *Size* (log of total assets), *Equity ratio* (equity-to-asset ratio), *Liquid assets* (cash plus marketable securities divided by total assets), *Wholesale funding* (large-denomination certificates of deposits, brokered deposits, and Federal funds purchased and securities sold under repurchase agreements divided by total assets), *C&I loans* (commercial and industrial loans to total assets), *Tier 1 ratio* (tier 1 capital to total risk-weighted assets ratio), and *Charter type* that indicates whether a bank is national or state charted. Bank-level financial controls are measured in one-year-lag period. Some specifications also control for county-specific traits, including *Log* p*opulation*, *Income per capita*, *Labor market participation*, and *Employment*, using data from the Personal Income and Employment Table of Bureau of Economic Analysis (BEA).

III. Empirical Design

To establish a casual impact of bank liquidity conditions on the outcome of small business lending, as well as the consequent business creation, employment, and personal income, we exploit the liquidity windfalls to local bank branches resulting from the shale development by the oil and gas sector since the technological advancements in fracking. We now describe the background of our identification strategy in more detail, followed by how we construct bank-specific, time-varying measures on the exposure to shale liquidity shocks.

3.1 Fracking and identification strategy

Our identification strategy exploits the technological breakthrough that combines horizontal drilling with hydraulic fracturing (fracking) in the U.S. oil and natural gas sector in the early 2000s. Mitchell Energy is the pioneering company that initially discovered the technological innovation when drilling the Barnett Shale Play of Texas. After two decades of experiments since the early 1980s, Mitchell found that fracking enables developers to break apart the highly non-porous rock of shale formations, freeing natural gas trapped inside the rock (Yergin, 2011; Gold, 2014). The Barnett Shale began to produce vast quantities of shale gas after Devon bought Mitchell Energy and combined slick-water fracking with horizontal drilling in late 2002, making shale gas production economically viable. We therefore treat 2003 as the first year when oil and gas companies started applying fracking to shale drilling activities.

Fracking has changed the conventional wisdom on shale gas production and shifted the energy landscape in the U.S. Shale gas has nowadays become the nation's leading source of nonconventional energy. According to the Annual Energy Outlook (AEO 2016) released by the Energy Information Administration (EIA), nearly half of total U.S. natural gas production in 2015 comes from shale gas production. As a comparison, the share of hydrocarbon produced from shale wells was less than 1% in 1999 when shale production was not commercially accessible. Due to the technological advancements that facilitate shale development, the U.S. is estimated to have vast amount of shale reserves: it is estimated to have 200 trillion cubic feet (tcf) of proved shale gas resources, plus 623 tcf of additional unproved yet technically recoverable shale gas resources.[3] Combined together, a total 823 tcf of shale gas is enough to fulfill the entire nation's gas consumption for at least 30 years.

The shale drilling activities bring material liquidity windfalls to local bank branches, which we exploit as positive shocks to bank liquidity conditions. More specifically, oil and gas companies need to obtain mineral leases from local landowners before conducting drilling operations. The mineral leases typically involve a large upfront bonus based on the number of acres leased out plus a royalty depending on extracted resources from the lease. Property owners who receive large leasing payments from developers then deposit in their local branches, leading to a positive liquidity shock to banks. Anecdotal evidence suggests that the shale liquidity windfalls to banks

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

are nontrivial. According to Plosser (2015), for instance, leasing contracts use bonus varying from $10 to $30,000 per acre, and a royalty percentage ranging from 10% to 25%. Thus, a property owner who leases out one square mile of land (equivalent to 640 acres) at an average value of $15,005 per acre would receive an upfront payment of $9.6 million plus future monthly royalties. We provide evidence below that validates our empirical setting: banks that are exposed to shale development experience a material increase in deposits.

The shale development results in plausible exogenous liquidity windfalls for banks for several reasons. First, technological advancements in shale gas production were unexpected. Second, given that extracting shale gas is difficult and expensive (Lake et al., 2013), the economic viability of producing shale has is often driven by broader macroeconomic factors, such as demand for natural gas and prices of natural gas, not local economic conditions (Gilje, Loutskina, and Strahan, 2016). Third, given that (a) the discoveries of shale formations in different geographies are unpredictable: it is difficult even for the energy companies to predict the existence of shale resources, and (b) the process of mineral leasing usually occurs very rapidly, it is unlikely for banks to adjust their branch networks so as to gain larger exposure to shale liquidity shocks. Nevertheless, we construct an instrument that purge the time-series variations in a bank's branch networks since 2003. We describe our instrumental variable in more detail in Section 3.3.

3.2 Well data and bank branch networks

We combine data of shale wells across the U.S. with detailed information on bank branch structure, to construct time-varying, bank-specific exposure to shale liquidity shocks. First, we obtain a unique and comprehensive U.S. well database from the IHS Markit Energy, which covers almost every well drilled in the U.S. over the period of 2000 – 2014. Each well is uniquely identified with 14-digit American Petroleum Institute (API) number. IHS contains detailed information on the spud date, location, and well orientation for more than 100,000 shale wells drilled in the U.S. since 2003, the beginning year of our sample period. Second, we extract bank branch structure data from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD) database, which provides information, for each bank branch, on its geographic locations and deposit balances as of June 30 of each year since 1994.

3.3 Shale liquidity shock measure

To measure the extent to which banks are exposed to the shale-induced liquidity shocks, we first calculate the number of shale wells drilled in each county during a year. Following existing 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.

We then calculate the number of branches that are located in counties with the shale development activities, where the number of branches in a county is weighted by the intensity of liquidity windfalls received by that bank in that particular county. Formally,

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

where *b*, *j*, *t* represent bank, county, and year. $Branches_{b,j,t}$ is the number of branches bank *b* owns in county *j* in year *t*; $Wells_{j,t}$ denotes the cumulative number of shale wells drilled in county *j* from 2003, the onset of shale development, to year *t*; $Mktshr_{b,j,t}$ represents the market share of deposits owned by bank b in county j in year *t*; $Branches_{b,t}$ represents the total number of branches owned by bank *b* at time *t*. Assuming that the shale-induced liquidity shocks received by a bank in a county is proportional to the bank's market share in that particular county, our measure is designed to capture a bank's exposure to shale liquidity shocks through its branch networks across counties. *Shale liquidity shock* equals to zero for banks with branches located in counties without any wells, and increases from zero to positive numbers as counties laying within a bank's branch network have shale wells drilled over time. Table 1 Panel C shows that our bank liquidity shock measure, *Shale liquidity shock*, has a sample mean value of 0.5. Among those banks with positive liquidity shocks, the sample average value equals 1.7.

Although banks are unlikely to alter their branch networks to gain greater exposure to shale liquidity shocks given the nature of shale development process, we nevertheless construct an instrument for *Shale liquidity shock* to further alleviate this concern. Specifically, we design an instrument that relies only on a bank's branch structure in 2002, the year before the technological breakthroughs that facilitate shale development. As not even the energy companies anticipated technological innovations in fracking before 2003, banks could not have expected the advent of shale development back in 2002. 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* represent bank, county, and year. $Branches_{bj,2002}$ equals the number of branches owned by bank *b* in county *j* in 2002; $Wells_{jt}$ denotes the cumulative number of shale wells drilled in county *j* from 2003 to *t*; $Mktshr_{b,j,2002}$ equals the market share of deposits of bank *b* in county *j* in year 2002; $Branches_{b,2002}$ equals the total number of branches owned by bank *b* in 2002. This instrumental variable, *Shale liquidity shock preexisting branches*, measures a bank's exposure to shale drilling activities using its preexisting branch networks in 2002. In our context, to the extent that banks could not have anticipated the shale boom in 2002, our instrument is plausibly orthogonal to bank characteristics that affect small business lending decisions. The first-stage regression results of our 2SLS analyses below show that *Shale liquidity shock preexisting branches* is strongly, positively correlated with *Shale liquidity shock*, suggesting that we do not have a weak instrument problem.

3.4 Validity tests

The key assumption underlying our identification strategy is that shale development brings material liquidity inflows to local bank branches, since landowners deposit their lucrative leasing income into nearby branches. We use the following regression models to formally test this channel.

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

where b, t represent bank, and year. The dependent variable, $Deposit\ growth_{b,t}$, is the growth rate of deposits of bank b in year t. The key explanatory variable, $Liq_{b,t}$, denotes the measure of *Shale liquidity shock* of bank b in year t. $\Pi_{b,t-1}$ represents an array of bank traits, namely *Bank size*, *Equity ratio*, *Liquid assets*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, and *Charter type*, all measured at the end of year *t-1*. Meanwhile, we include 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 clustered at the bank level.

Table 2 reports the regression results of bank deposits on the measure of bank liquidity shocks, suggesting that banks exposed to shale development experience significant liquidity windfalls relative to banks that did not receive the shock. As shown in column (2), *Shale liquidity shock* enters the regression positively and significantly at the 1% level. The economic magnitude is large. The coefficient estimate on *Shale liquidity shock* from the OLS regression in column (2) suggests that deposits growth of a bank with an "average" exposure to shale liquidity shocks (*Shale liquidity shock* = 1.7) is higher than that of a bank that did not receive the liquidity shock (*Shale liquidity shock* = 0) by 1.36 percentage points. The economic magnitude is large, as it amounts to about 16% of the sample mean of *Deposit growth* (0.086).

The results are robust when we estimate the model using 2SLS with *Shale liquidity shock preexisting branches* as the instrument. The first stage regression results reported in column (1) show that the instrumental variable, *Shale liquidity shock preexisting branches*, enters positively and significantly. The F-statistic of the null hypothesis that the instrument is irrelevant is 340, easily passing the threshold of relevance tests. The coefficient on *Shale liquidity shock* in the second stage regression barely changes as reported in column (3).

Furthermore, Table 2 columns (4) – (9) redo the analyses while looking into the impact of liquidity shocks on three individual components of total deposits, namely (a) retail deposits, (b) time deposits of $100,000 or more, and (c) brokered deposits. *Retail deposits* are defined as total deposits minus time deposits of $100,000 or more and brokered deposits; *Brokered deposits* are 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.

If bank liquidity windfalls result primarily from property owners depositing mineral leasing payments into local bank branches, we expect the effects to be significant only on retail or time deposits, not brokered deposits. Columns (4) – (9) results are fully consistent with this expectation: the coefficients on *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*. The findings are robust to using either OLS or 2SLS.

IV. Results

In this section, we report and discuss our empirical results of the impact of shale liquidity shocks on small business lending, and real outcomes of small business creation and exit, and employment. Depending on the specific outcome variables constructed from different datasets, we conduct empirical analyses at alternative levels, including the loan, bank-county-year, county-by-year, and county-by-industry-by-year level. We describe the model specifications before we present the corresponding results.

4.1 SBA loan outcomes

Exploiting the loan outcomes from SBA loan contract dataset, we start our analyses by evaluating the impact of bank liquidity shocks on specific loan contract terms, while differentiating borrowers by their business types: whether a borrower is an existing business, or whether the size of a borrower (in terms of the employee number) exceeds a certain threshold. The model specification at the loan-level is as follows.

$$SBL_{l,b,f,i,j,t} = \beta_0 + \beta_1 Liq_{b,t} + \beta_2 Liq_{b,t} * Btype + \beta_2{}' \Pi_{b,t-1} + \beta_3{}' \Theta_{f,t-1} + \alpha_{b,i,j,Btype} + \alpha_{i,j,t} (or\ \alpha_{j,t}) + \varepsilon_{l,b,f,i,j,t}, \quad (4)$$

where the dependent variable, $SBL_{l,b,f,i,j,t}$, denotes the specific contract term (i.e., *Loan amount*, *Interest rate*, or *Maturity*) of loan *l* made by bank *b* to borrowing firm *f* in industry *i*, county of location *j*, and year *t*. $Liq_{b,t} * Btype_{f,t-1}$ is the interaction of *Shale liquidity shock* of bank *b* at time *t* and the business type of borrower *f* at time *t*-1. We divide borrowers into different business types based on (a) whether a borrower is an existing business, or (b) whether a borrower's employee number is above or equal to five.[4] $\Pi_{b,t-1}$ denotes an array of bank traits, namely *Size*, *Equity ratio*, *Liquid assets*, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, and *Charter type*; $\Theta_{f,t-1}$ denotes a vector of borrower characteristics including *Business organization* (proprietorship, partnership, or corporation), *Employee size*, and *Existing business*.[5] Meanwhile, we include bank-county-industry-(two-digit NAICS)-Btype fixed effects ($\alpha_{b,i,j,Btype}$) to account for any unobservable, time-invariant factors that might influence a bank's lending decisions to businesses across counties, industries, and borrower types. Thus, our empirical analyses essentially compare the small business loan outcomes by two otherwise similar banks to borrowers with the same business type, in the same industry, and located in the same county. In addition, we control for

[4] We choose this cutoff to make it consistent with our later analyses on the net creation of small businesses, as CBP data reports the aggregate number of establishments using size categories of 1-4, 5-9, 10-19, etc. Moreover, the median value of borrower employment size in our loan sample equals four, and our results remain robust if we use four as the alternative cutoff of the employee size.
[5] Note, the linear term of *Btype* is subsumed in the bank-county-industry-Btype dummies, and is thereby omitted from the specification model.

county-industry-year ($\alpha_{i,j,t}$) or county-year ($\alpha_{j,t}$) fixed effects to condition out time-varying factors across county-by-industry or counties. As mentioned, our loan-level analyses focus on small business borrowers located in non-shale counties to isolate the supply side effects from the potential demand-side effects associated with shale development. We estimate Equation (4) using 2SLS and instrument *Shale liquidity shock* and *Shale liquidity shock * Btype* with *Shale liquidity shock preexisting branches* and *Shale liquidity shock preexisting branches * Btype*.

Table 3 reports the 2SLS regression results of *Loan amount* on lenders' liquidity shocks while differentiating borrowers by business types, using Equation (4) as the specification model. The interaction of the time-varying, bank-specific liquidity shock measure and the indicator of existing business, *Shale liquidity shock * Existing business*, enters the regressions positively and significantly in all specifications of columns (1) – (3), whereas coefficient estimates of the linear term, *Shale liquidity shock*, are negative and statistically insignificant. These results are consistent with the view that shale liquidity shocks increase loan size only for borrowers that are likely to have tract records, but not to newly-created establishments. The economic difference between these two types of groups is large. Coefficients from column (3) imply that increases in the average loan amount resulting from banks' exposure to an "average" shale liquidity shock (1.7) to existing businesses are 11% (= 0.065*1.7) higher than those to new borrowing businesses.

Table 3 columns (4) – (6) results suggest that the loan-size-increasing effects of bank liquidity windfalls are significant only among borrowers with employee number exceeding five, not those with very small employee size. Again, we evaluate the differential effects of shale liquidity shocks on loan size by interacting *Shale liquidity shock* with an indicator that equals one if a business's employee number is equal to or greater than five, and zero otherwise (*Employee ≥ 5*). As shown, the coefficient estimates on the interaction term, *Shale liquidity shock * Employee ≥ 5*, are positive and statistically significant at the 1% level in all specifications. The linear term, *Shale liquidity shock*, enters the regressions insignificantly. Estimates from column (6) suggests that banks exposed to shale liquidity shocks (1.7) increase small business lending amounts more to businesses with employee number exceeding five by 7% (= 0.042*1.7) than to borrowers with employee size less than five.

To illustrate the economic magnitude, consider a hypothetical "average" bank that received shale liquidity shocks of 1.7, and the other bank not exposed to such liquidity shocks. While the SBA loan size made by the former bank is on average greater than that of latter one, the difference in the loan size between these two banks is 11% (7%) higher among existing businesses (business with more than five employees) than new ones (those with less than five employees). This is equivalent to about $24,750 ($15,750) in the dollar amount of loan size.

The results obtain when we control for bank-county-industry-type, and county-industry-year (or county-year) fixed effects, together with a set of borrower characteristics (i.e., *Business organization*, *Employee size*, and *Existing business*), and bank traits (*Size*, *Equity ratio*, *Liquid assets*,, *Wholesale funding*, *C&I loans*, *Tier 1 ratio*, and *Charter type*).

In addition to loan size, we examine the impact of bank liquidity gains on two other terms of loan contracts: *Interest rate* and *Maturity*, where we differentiate borrowers based on whether they are existing business or whether employee number exceeds five. Using the same loan-level specification as in Table 3, Table 4 suggests that the shale liquidity shocks on average lowers the interest rate, and more importantly, the price-reducing effects of lenders' liquidity shocks are more pronounced among businesses with more than five employee. As shown in columns (4) – (6), the interaction of *Shale liquidity shock* and the indicator of *Employee* $\geq$ *5* enters the regressions negatively and significantly, indicating that the spread-reducing effects of bank liquidity windfalls are more prominent for relatively larger borrowing businesses. The impact of liquidity shocks on loan price does not seem to differ across borrowers with existing or new businesses, as suggested in columns (1) – (3). Economically, coefficients reported in column (6) suggest that banks that experienced liquidity windfalls would lower the interest rate of loans to more-than-five-employee business more by about 5.6 basis points (= 0.039*1.7) than those to less-than-five-employee business.

Focusing on loan maturity, Table 5 shows that liquidity gains induce banks to extend SBA loans with longer maturities, especially among borrowers that already established their businesses at the time of loan originations. As shown in columns (1) – (3), the key variable of interest, *Shale liquidity shock * Existing business*, enters the regressions positively and significantly at the 1% level, and the linear term of *Shale liquidity shock* enters the regressions positively and insignificantly. Columns (4) – (6) show that the effect on loan maturity varies with borrower employment size. Combined together, Table 4 and 5 results suggest that banks with liquidity shocks use favorable loan terms only to borrowers that either have established businesses and thus trackable past performance or have a relatively bigger size. The findings are consistent with the view that lower interest rates and longer maturities are substitute: banks tend to reduce interest rates for relatively larger borrowers, while extend loan maturities for those with trackable past performance.

4.2 Aggregate small business lending

To assess the impact of shale liquidity shocks on banks' aggregate amount of small business lending, we construct each bank's aggregate lending from two complementary data sources: (a) the aggregated SBA loan amount and number, and (b) the aggregate volume of small business loans directly from CRA dataset. While SBA data provides information on borrowers' characteristics, such as the types of businesses and industries, it represents a subset of small business lending by commercial banks in the U.S. We therefore use a second CRA database that represents the vast majority small business lending by U.S. banks. Consistent with the SBA loan-level analyses, we differentiate borrowers based on their types of business (i.e., *Existing business* or *Employee size*). For the aggregate amount and number of SBA loans, we use the following model specifications to conduct analyses at the bank-county-type-year or the bank-county-industry-type-year level.

$$L_{b,j,Btype,t}\ (L_{b,j,i,Btype,t}) = \varphi_0 + \varphi_1 Liq_{b,t} + \varphi_2 Liq_{b,t} * Btype + \varphi_2{}' \Pi_{b,t-1} + \alpha_{b,j,Btype}\ (\alpha_{b,j,i,Btype}) + \alpha_{j,t}\ (\alpha_{j,i,t}) + \varepsilon_{b,j,Btype,t}\ (\varepsilon_{b,j,Btype,i,t}), \quad (5)$$

where the dependent variable, $L_{b,j,Btype,t}$ ($L_{b,j,i,Btype,t}$), denotes the aggregate number or amount of SBA loans made by bank *b* to borrowers with certain business types in county *j*, (industry *i*,) and year *t*. Btype represents the group of borrowers' business type, an indicator of *Existing business* or *Employee ≥ 5*. Other variables are defined the same as in Equation (4). We include bank-county-type (bank-county-industry-type) fixed effects to condition out time-invariant differences across banks, counties, (industries,) and the type of borrower businesses, and county-year (county-industry-year) fixed effects to account for time-varying differences across counties (county-by-industry). Focusing on the aggregate small business lending in non-shale counties only, we estimate Equation (5) using 2SLS and instrument *Shale liquidity shock* and *Shale liquidity shock * Btype* with *Shale liquidity shock preexisting branches* and *Shale liquidity shock preexisting branches * Btype*.

Table 6 reports the estimation results of shale liquidity shocks on the aggregate amount and number of SBA loans while differentiating loans by borrowers' business types. The dependent variable is the aggregate SBA loan amount in Panel A, the aggregate loan number in Panel B. Columns (1) and (2) divide loans based on whether a borrower is an existing business or a new one, and columns (3) and (4) differentiate loans by whether a borrower's employee size exceeds five or not. Columns (1) and (3) report the analyses results at the bank-county-type-year level, while columns (2) and (4) report the results at the bank-county-industry- type-year level. As shown, the instrumented *Shale liquidity shock * Btype* (*Existing business* or *Employee ≥ 5*) enters positively and significantly at the 1% level in all specifications of Table 6, suggesting that liquidity windfalls enhance SBA loan volumes, with the effects more pronounced for borrowers that have an established existing business or those with a relatively large employee size.[6]

[6] The impact of bank liquidity shocks on SBA lending is not driven by differences in government guarantee. Appendix Table A1 reports the robustness tests on the effects of shale liquidity shocks on SBA lending outcomes. As shown,

We confirm our findings using a second data source from CRA, which covers the majority bank lending to small and medium enterprises in the U.S. The formal specification we employ is as follows.

$$L_{b,j,t} = \varphi_0 + \varphi_1 Liq_{b,t} + \varphi_2{}' \Pi_{b,t-1} + \alpha_{b,j} + \alpha_{j,t} + \varepsilon_{b,j,t}, \quad (6)$$

where the unit of analysis is at the bank-county-year level; the dependent variable, $L_{b,j,t}$ denotes the aggregate number or amount of CRA small business loans of bank *b* in county *j* during year *t*. $Liq_{b,t}$ represents the same *Shale liquidity shock* that captures the extent to which bank *b* is exposed to the shale liquidity shocks in year *t*. The model includes a set of time-varying bank characteristics ($\Pi_{b,t-1}$), bank-county fixed effects to condition out any time-invariant differences across bank-county, and county-year dummies to account for time-varying factors across counties (such as local economic conditions).

Table 7 reports the results of the effects of bank liquidity shocks on the aggregate amount (Panel A) and number (Panel B) of small business lending from CRA dataset. We examine the effects on three groups of CRA lending, depending on the loan size of lower than $100,000 or less (columns (1) – (3)), between $100,000 and $250,000 (columns (4) – (6)), and more than $250,000 and below one million (columns (7) – (9)). Within each loan size group, we estimate the model of Equation (6) using OLS and 2SLS where we instrument *Shale liquidity shock* with *Shale liquidity shock preexisting branches*. And, we mitigate the concern that our results are confounded by shifts in local economic conditions resulting from the shale development itself, by repeating the 2SLS analyses on a sample of CRA lending in counties where no shale drilling activity has occurred since 2003.

our bank liquidity shock measure is not correlated with the SBA guarantee ratio (columns (1) and (2)). And, columns (3) – (6) suggest that the effects on SBA lending are consistently more pronounced among large and existing businesses, when we use a sample of SBA Express Program that has a maximum guarantee ratio of 50% (in fact almost all SBA Express loans are guaranteed at 50%).

Table 7 results show that banks exposed to positive liquidity shocks increase subsequent small business lending that falls into the largest loan size category, but no effects on the other two smaller loan size categories. As can be seen from in columns (7) – (9), *Shale liquidity shock* enters positively and significantly in all the specifications of the loan size group between $250,000 and one million. Coefficients from column (9) of Panel A indicate that banks exposed to an average shale liquidity shock would increase the amount of small business lending with loan size above $250,000 by about 10.7% (=0.063*1.7). In contrast, the coefficients on *Shale liquidity shock* are statistically insignificant and economically small in the loan size groups below $250,000, as shown in columns (1) – (6). To the extent that the loan size reflects the size of the borrowing business, findings in Table 7 are consistent with our loan-level results: bank liquidity windfalls translate into a greater amount of small business lending disproportionately more to businesses with relatively bigger size.

4.3 Small business creation and exit, and job creation

Table 3 – 7 suggest that liquidity gains induce banks to increase small business lending that benefit primarily larger and existing businesses. We now investigate whether shale liquidity shocks that facilitate small business lending translate into real outcomes on the creation of small establishments, existing business expansion and employment growth, and business exit. The regression model used to evaluate the impact of aggregate liquidity gains on county-level changes in small establishments is as follows.

$$Est_{s,j,t} = \theta_0 + \theta_1 AvgLiq_{j,t} + \theta_2 AvgLiq_{j,t} * EmpSize_s + \theta_3{}'\mathrm{H}_{j,t-1} + \alpha_{s,j} + \alpha_t + \varepsilon_{s,j,t}, \quad (7)$$

where the dependent variable, $Est_{s,j,t}$, denotes the log number of small establishments with employee size class *s* in county *j* during year *t*. NETS data provides employee size for each establishment, allowing us to investigate the heterogeneous effects of liquidity shocks on the creation of small businesses with small versus large employee sizes. We focus on small business establishments with less than 50 employees, and $EmpSize_s$ is an indicator that equals one if the number of employees exceeds five, and zero otherwise.

$AvgLiq_{j,t}$ represents *Shale liquidity shock$_{County\text{-}Avg}$* for county *j* in year *t*. We define *AvgLiq* as the weighted average of bank-specific *Shale liquidity shock* across banks with branches in that particular county, with each bank weighted by its small business lending volumes in that county. *Shale liquidity shock$_{County\text{-}Avg}$* is designed to capture a county's exposure to shale liquidity shocks through bank branch networks, not liquidity shocks from actual shale development in that county. Thus, a county can have a positive value of *Shale liquidity shock$_{County\text{-}Avg}$* when banks exposed to shale liquidity shocks have branches located in that county, even if no shale wells have been drilled in that county. Figure 1 visually shows that our county-aggregate shale exposure measure varies across U.S. counties (represented by the red colors), especially those without any actual shale wells drilled. To mitigate the concern that local economic changes with the shale development activities, we exclude counties with shale wells drilled from our county-level analyses (represented by the blue colors). We exclude counties with shale wells drilled from our analyses to address the concerns that local economic conditions change with the shale development activities.

In similar vein, we construct the instrument of county-specific shale liquidity shocks, *Shale liquidity shock$_{County\text{-}Avg}$ - preexisting branches* (*AvgLiq preexisting branches* for short), defined as the weighted average of *Shale liquidity shock preexisting branches* across banks with branches located within a given county.

Equation (7) controls for a set of time-varying, county-specific traits ($\text{H}_{j,t-1}$) including *Log population, Income per capita*, *Labor market participation, Employment*, *Ratio of proprietor employment*, as well as the average of local banks' financial conditions, together with the county by establishment size, and time fixed effects to condition out time-invariant differences across establishment size class by county, and time trends. In this way, the coefficient θ_1 on *AvgLiq* captures the effects on the creation of small establishments with employee size lower than five between two otherwise similar counties, except for the extent to which their local bank branches are exposed to shale liquidity shocks; θ_2 on the interaction term, *AvgLiq*EmpSize*, captures the differential effects on the creation of small businesses with employee size greater than five.

Table 8 reports the second-stage regression results of the effects of aggregate shale liquidity shocks in a county on the creation of its small establishments in the NETS database, while differentiating by business size. The dependent variable is the log number of small establishments with employee size below 50 across columns in Table 8. Columns (1) – (3) conduct the analyses at the county by year level, whereas columns (4) – (6) at the county-industry by year level. As shown, the interaction of *Shale liquidity shock*$_{County\text{-}Avg}$ and *EmpSize* enters the regressions positively and significantly at the 1% level in columns (1) – (3) at the county aggregate, suggesting that a positive liquidity shock facilitates the creation of relatively large establishment, but not the small ones. The differential effects diminish when we aggregate *Small business creation* at the county-industry-level.

To assess the impact on business expansion and job creation, we employ the same specification as in Equation (7), and use *Employment growth* as the dependent variable. As shown in Table 9, while the linear term *Shale liquidity shock*$_{County\text{-}Avg}$ enters regressions insignificantly, its interaction with *EmpSize* enters the regressions positively and significantly at the 1% level across all columns of Table 9, suggesting that a county's exposure to shale liquidity shocks promotes small business growth and creates jobs, and, the effects are more pronounced among relatively large establishments. The coefficient estimates from column (1) indicate that employment grow faster by about 22 basis points (=0.0015*1.49) among relatively-large businesses in a county that receives an average liquidity shock. This is equivalent to 22% of sample average of *Employment growth*.

As a final set of tests, we evaluate the impact of liquidity shock on small business exit. Table 10 reports the regression results using Equation (7) with *Small business exit* as the dependent variable. The coefficient estimates on the linear term, *Shale liquidity shock*$_{County\text{-}Avg}$, are positive and statistically significant at the 1% level across columns, suggesting that very small businesses (with employee size below five) have a higher exit rate in counties that receive shale liquidity shocks than counties without the exposure. On the other hand, the interaction of *Shale liquidity* $shock_{County\text{-}Avg}$ and the indicator of large employee size enters negatively and significantly, suggesting that relatively large businesses (with employee size above five) exit at a lower rate in counties that are exposed to the positive liquidity shocks than counties without the exposure. Taken together, the increased exits of the smallest establishments could be the result of crowding-out by relatively larger ones (as larger ones are expanding and gaining greater market shares).

V. Conclusion

We assess the heterogeneous effects of bank liquidity conditions on small business lending across borrowers with different business size and age. We use a detailed SBA small business loan dataset that provides contract-level information, and the comprehensive NETS database that offers the coverage of all the U.S. establishments. To establish causality, we exploit exogenous liquidity shocks for local bank branches resulting from the shale development activities since 2003, the year of technological breakthroughs in fracking. Using a unique database that covers almost all the shale well data in the U.S., we construct a time-varying, bank-specific measure of the extent to which a bank is exposed to shale development via its branch networks. As we exclude borrowers located in counties with any shale development, our analyses are not driven by changes in local economic conditions resulting from the shale boom.

Our findings suggest in response to the shale-induced positive liquidity shock, banks provide favorable loan terms (greater loan size, lower interest rate, and longer maturity) to relatively large and established small businesses, not to very small and young startups. We further link the effects of credit provisions to SME with real outcomes on the creation, expansion, and exit of small businesses. Consistently, we find that positive liquidity shocks facilitate the creation of small businesses, spur the employment growth, and reduce business exit rates, and the effects much more pronounced among large and existing establishments, as opposed to small and new ones. Our study implies that banks are adequate to promote access to finance for some types of small business borrowers, but not necessarily for all.

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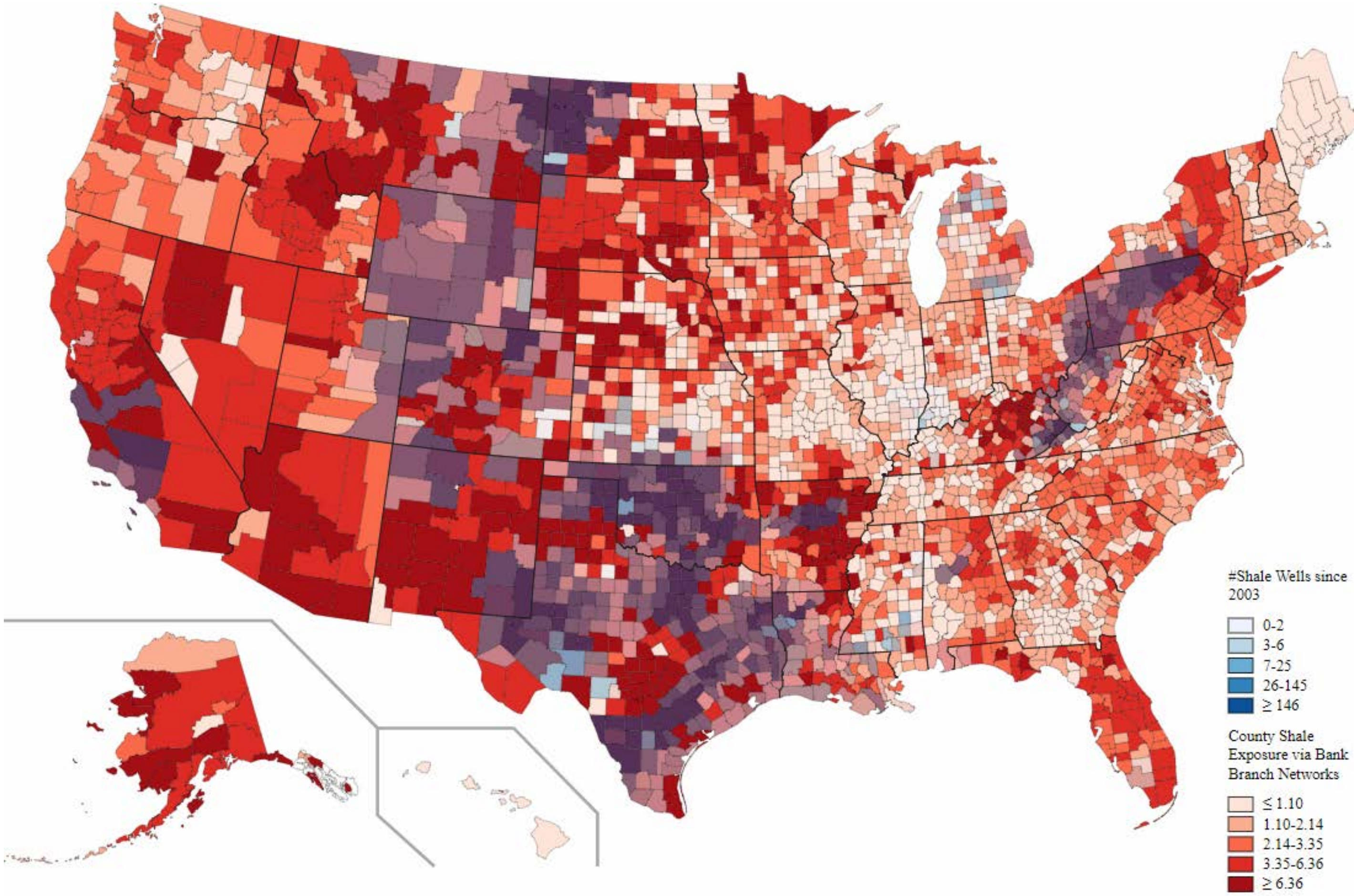

Figure 1. Shale Development VS. Shale Exposure via Bank Branch Networks, by U.S. County in 2014

Note: this figure is the heat map for two measures: the he blue color represents the number of actual shale wells drilled in a county as of 2014, and the red color represents the weighted average of bank-specific *Shale liquidity shock* across banks with branches in that particular county, with each bank weighted by its small business lending volumes in that county.

Table 1: Summary Statistics

This table reports summary statistics across banks and counties with/without exposure to the shale liquidity shock between 2003 and 2014. All statistics are sample mean values, with sample standard deviations in the parentheses. Column (1) reports statistics for the whole sample; Column (2) reports the banks that are exposed to the shale liquidity shock and Column (2) reports the unexposed banks. Counties with and without shale liquidity shock (exposed and unexposed counties) are reported in Column (4) and (5), respectively. Panel A reports the loan-level characteristics of the SBA 7a loan, including loan size, interest rate, and months of maturity. Panel B reports summary statistics for CRA small business lending by each bank to each county, including total dollar amount, loan number and average loan size. Panel C reports the shale exposure by the SBA sample banks, as well as their basic financial characteristics from the call reports. Panel D reports small business creation, measured as the log number of new establishments created in a county-industry-size-year group, and the expansion of existing small businesses, measured as the log change of employment of small businesses. Small businesses are defined as establishments with employment size below 50 and not branches or subsidiaries of any parent entities. Statistics in this panel is based on the NETS dataset. Panel E reports local banks' average shale-liquidity-shock exposure (weighted by market share of CRA lending) and basic economic conditions in the sample counties, including employment, average payroll, number of small establishments with employment size below 50, population, and per capita income from the BEA Local Area Personal Income accounts.

	Whole Sample	Exposed Banks	Unexposed Banks	Exposed Counties	Unexposed Counties
	(1)	(2)	(3)	(4)	(5)
Panel A. CRA lending (Bank-County-Year Level)					
Loan Size (in $k)	225	210	251	302	215
	(393)	(370)	(428)	(476)	(380)
Interest Rate	7.60	7.90	7.11	7.53	7.61
	(2.07)	(2.19)	(1.75)	(2.14)	(2.06)
Months of maturity	102	100	105	116	100
	(71)	(69)	(74)	(82)	(69)
Obs.	439,272	273,110	166,162	52,180	387,092
Panel B. CRA lending (Bank-county-year level)					
Total Loan Amount (in $k)	2,935	4,027	1,938	3,059	2,918
	(15,872)	(20,659)	(9,490)	(26,515)	(13,755)
No. Loans	71	48	92	78	70
	(559)	(436)	(651)	(1,100)	(433)
Avg. Loan Size	108	135	82	99	109
(in $k)	(171)	(180)	(159)	(166)	(172)
Obs.	905,434	432,284	473,150	110,489	794,945

Table 1: Summary Statistics (Continued)

	Whole Sample	Exposed Banks	Unexposed Banks	Exposed Counties	Unexposed Counties
	(1)	(2)	(3)	(4)	(5)
Panel C. Bank Characteristics (Bank-Year Level)					
Shale liquidity shock	0.497	1.709	0.000		
	(2.185)	(3.789)	0.000		
Deposit growth	0.086	0.095	0.082		
	(0.16)	(0.17)	(0.15)		
Bank size	12.82	13.40	12.58		
	(1.42)	(1.78)	(1.16)		
Equity ratio	0.101	0.101	0.100		
	(0.029)	(0.029)	(0.028)		
Liquid assets	0.233	0.253	0.224		
	(0.118)	(0.128)	(0.113)		
Wholesale funding	0.209	0.206	0.210		
	(0.127)	(0.120)	(0.129)		
C&I loans	0.119	0.126	0.116		
	(0.074)	(0.073)	(0.074)		
Tier 1 ratio	0.129	0.129	0.129		
	(0.042)	(0.041)	(0.042)		
Obs.	13,989	4,065	9,924		
Panel D. Business Dynamics (County-Ind-Size-Year Level)					
Small Business Creation	0.659			0.608	0.666
	(1.164)			(1.115)	(1.170)
Employment Growth	0.010			0.010	0.010
	(0.124)			(0.126)	(0.112)
Small Business Exit	0.050			0.054	0.050
	(0.127)			(0.133)	(0.127)
Obs.	2,712,043			346,953	2,365,090
Panel E. County characteristics (County-Year Level)					
Shale liquidity shock $_{\text{County-Avg}}$	1.494			3.935	1.136
	(2.768)			(4.898)	(2.065)
No. Small Establishments	6,729			7,185	6,660
	(23,403)			(40,413)	(19,595)
Population (in k)	97			99	97
	(312)			(537)	(262)
Per Capita Income (in $k)	32.5			33.7	32.3
	(9.56)			(9.76)	(9.51)
Obs.	33,901			4,443	29,458

Table 2: Shale Liquidity Shock and Bank Deposits

This table reports bank-level regression results which show the effects of shale liquidity shock on bank deposits. The first column reports the first-stage regression result and the rest columns report the OLS results (Columns 2, 4, and 6) or 2SLS results for the second stage of the IV regressions (Columns 3, 5, and 7). The dependent variable is the log value of total deposits (Columns 2 and 3), retail deposits (Columns 4 and 5), time deposits with size above $100,000 (Columns 6 and 7), or brokered deposits (Columns 8 and 9). All columns control for lagged bank characteristics including log asset, equity/asset ratio, liquidity ratio, deposit/asset ratio, wholesale funding/asset ratio, C&I loan/asset ratio, and tier 1 ratio. Bank and year fixed effects are also controlled. Standard errors are clustered at bank level. *, **, and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	First Stage	Second Stage							
		Total Deposits		Retail Deposits		Time Deposits >$100k		Brokered Deposits	
		OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Shale liquidity shock, 2002 branch network	0.940***								
	(0.018)								
Shale liquidity shock		0.008***	0.007***	0.005***	0.005**	0.014***	0.016***	0.032	0.028
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.021)	(0.023)
Bank Char. t-1	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.	13,989	13,989	13,989	13,989	13,989	13,989	13,989	13,989	13,989
R^2	0.95	0.53	0.53	0.24	0.24	0.41	0.41	0.18	0.18

Table 3: Bank Liquidity and SBA Loan Size across Borrower Types

This table reports the 2SLS IV regression results for the effects of bank exposure to the shale liquidity shock on SBA 7a loan size across different borrower types in unexposed counties. The dependent variable is the log dollar amount of the originated SBA 7a loans. In the first three columns, bank shale exposure is interacted with the dummy indicator whether the borrower is an existing business. In the last three columns, bank shale exposure is interacted with the dummy indicator whether the borrower has more than 5 employees. All regressions control for lagged bank financial characteristics and bank-county-industry-type fixed effects. Borrower characteristics are controlled in Columns 2, 3, 5, and 6, including employee size, organization structure and new/existing indicator. Columns 1, 3, 4, and 6 control for county-industry-year fixed effects while Columns 2 and 5 control for county-year fixed effects. Standard errors are clustered at bank level. *, **, and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	New vs. Existing Businesses			Emp Size Below vs. Above 5		
	(1)	(2)	(3)	(4)	(5)	(6)
Shale liquidity shock	-0.022*	-0.014	-0.016	0.011	0.013	0.011
	(0.014)	(0.012)	(0.013)	(0.021)	(0.019)	(0.019)
Shale liquidity shock	0.083***	0.066***	0.065**			
× Existing business	(0.027)	(0.025)	(0.026)			
Shale liquidity shock				0.046***	0.043***	0.042***
× Employee≥5				(0.006)	(0.004)	(0.005)
Borrower Char. t-1		Y	Y		Y	Y
Bank Char. t-1	Y	Y	Y	Y	Y	Y
Bank-County-Ind-Type FE	Y	Y	Y	Y	Y	Y
County-Year FE		Y			Y	
County-Ind-Year FE	Y		Y	Y		Y
Obs.	387,092	387,087	387,087	387,092	387,087	387,087
R^2	0.57	0.57	0.61	0.60	0.58	0.61

Table 4: Bank Liquidity and SBA Interest Rate

This table reports the 2SLS IV regression results for the effects of bank exposure to the shale liquidity shock on SBA 7a interest rate across different borrower types in unexposed counties. In the first three columns, bank shale exposure is interacted with the dummy indicator whether the borrower is an existing business. In the last three columns, bank shale exposure is interacted with the dummy indicator whether the borrower has more than 5 employees. All regressions control for lagged bank financial characteristics and bank-county-industry-type fixed effects. Borrower characteristics are controlled in Columns 2, 3, 5, and 6, including employee size, organization structure and new/existing indicator. Columns 1, 3, 4, and 6 control for county-industry- year fixed effects while Columns 2 and 5 control for county-year fixed effects. Standard errors are clustered at bank level. *, **, and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	New vs. Existing Businesses			Employee Size Below vs. Above 5		
	(1)	(2)	(3)	(4)	(5)	(6)
Shale liquidity shock	0.041**	0.032*	0.038*	0.021	0.015	0.018
	(0.020)	(0.019)	(0.020)	(0.018)	(0.015)	(0.016)
Shale liquidity shock	-0.068*	-0.057	-0.060			
× Existing business	(0.037)	(0.035)	(0.037)			
Shale liquidity shock				-0.042***	-0.037***	-0.039***
× Employee≥5				(0.009)	(0.005)	(0.008)
Borrower Char. t-1		Y	Y		Y	Y
Bank Char. t-1	Y	Y	Y	Y	Y	Y
Bank-County-Ind-Type FE	Y	Y	Y	Y	Y	Y
County-Year FE		Y			Y	
County-Ind-Year FE	Y		Y	Y		Y
Obs.	387,092	387,087	387,087	387,092	387,087	387,087
R^2	0.65	0.62	0.66	0.66	0.63	0.66

Table 5: Bank Liquidity and SBA Loan Maturity

This table reports the 2SLS IV regression results for the effects of bank exposure to the shale liquidity shock on SBA 7a loan maturity across different borrower types in unexposed counties. The dependent variable is the number of maturity in months. In the first three columns, bank shale exposure is interacted with the dummy indicator whether the borrower is an existing business. In the last three columns, bank shale exposure is interacted with the dummy indicator whether the borrower has more than 5 employees. All regressions control for lagged bank financial characteristics and bank-county-industry-type fixed effects. Borrower characteristics are controlled in Columns 2, 3, 5, and 6, including employee size, organization structure and new/existing indicator. Columns 1, 3, 4, and 6 control for county-industry-year fixed effects while Columns 2 and 5 control for county-year fixed effects. Standard errors are clustered at bank level. *, **, and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	New vs. Existing Businesses			Emp Size Below vs. Above 5		
	(1)	(2)	(3)	(4)	(5)	(6)
Shale liquidity shock	1.000	1.108	1.098	2.278	2.226	2.278
	(1.063)	(1.034)	(1.069)	(1.474)	(1.385)	(1.466)
Shale liquidity shock× Existing business	1.773***	1.501***	1.573***			
	(0.518)	(0.441)	(0.475)			
Shale liquidity shock× Employee≥5				0.053	-0.072	-0.014
				(0.251)	(0.234)	(0.252)
Borrower Char. t-1		Y	Y		Y	Y
Bank Char. t-1	Y	Y	Y	Y	Y	Y
Bank-County-Ind-Type FE	Y	Y	Y	Y	Y	Y
County-Year FE		Y			Y	
County-Ind-Year FE	Y		Y	Y		Y
Obs.	387,092	387,087	387,087	387,092	387,087	387,087
R^2	0.56	0.51	0.56	0.56	0.52	0.57

Table 6: Bank Liquidity and aggregate SBA Lending

This table reports 2SLS IV regression results for the effects of bank exposure to the shale liquidity shock on aggregate SBA 7a small business lending across different borrower types in unexposed counties. The dependent variable is the log amount of total (Panel A) or the log number of loans (Panel B). Columns 1 and 3 show regression results at bank-county level, while Columns 2 and 4 show results at bank-county-industry level. In the first two columns, bank shale exposure is interacted with the dummy indicator whether the borrower is an existing business. In the last two columns, bank shale exposure is interacted with the dummy indicator whether the borrower has more than 5 employees. Lagged bank financial characteristics are controlled in all regressions, including log asset, equity/asset ratio, liquidity ratio, deposit/asset ratio, wholesale funding/asset ratio, C&I loan/asset ratio, and tier 1 ratio. Bank-county-type (here type means existing or new, or employee size below or above 5) and county-year fixed effects are controlled in Columns 1 and 3, and Bank-county-industry-type and county-industry-year fixed effects are controlled in Columns 2 and 4. Standard errors are clustered at bank level. *, **, and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	New vs. Existing Businesses		Emp Size Below vs. Above 5	
	(1)	(2)	(3)	(4)
Panel A. Total loan amount				
Shale liquidity shock	0.000	-0.024	0.016	-0.002
	(0.035)	(0.018)	(0.035)	(0.025)
Shale liquidity shock	0.050***	0.059***		
× Existing business	(0.014)	(0.006)		
Shale liquidity shock			0.058***	0.054***
× Employee≥5			(0.009)	(0.012)
Bank Char. t-1	Y	Y	Y	Y
Bank-County-Type FE	Y		Y	
Bank-County-Ind-Type FE		Y		Y
County-Year FE	Y		Y	
County-Ind-Year FE		Y		Y
Obs.	121,457	242,719	123,778	246,593
R^2	0.65	0.69	0.66	0.69
Panel B. Total loan number				
Shale liquidity shock	0.013	0.000	-0.017**	-0.020***
	(0.018)	(0.013)	(0.008)	(0.007)
Shale liquidity shock	-0.035	-0.028*		
× Existing business	(0.022)	(0.017)		
Shale liquidity shock			0.024***	0.015***
× Employee≥5			(0.004)	(0.005)
Bank Char. t-1	Y	Y	Y	Y
Bank-County-Type FE	Y		Y	
Bank-County-Ind-Type FE		Y		Y
County-Year FE	Y		Y	
County-Ind-Year FE		Y		Y
Obs.	121,457	242,719	123,778	246,593
R^2	0.71	0.7	0.72	0.69

Table 7: Bank Liquidity and CRA Small Business Lending

This table reports the bank-county-level 2SLS IV regression results which show the effects of bank exposure to the shale liquidity shock on CRA small business lending. The dependent variable is the log amount of annual CRA lending by each bank to each county (Panel A) or the log number of CRA loans (Panel B). Columns 1-2 show results for loans with size no larger than $100,000, Columns 3-4 for loans with size between $100,000 and $250,000, and Columns 5-6 for loans with size above $250,000. Columns 1, 3, and 5 report results for the whole sample, and Columns 2, 4, and 6 report results for only counties that do not experiene shale liquidity shock (unexposed counties). Lagged bank financial characteristics are controlled in all regressions, including log asset, equity/asset ratio, liquidity ratio, deposit/asset ratio, wholesale funding/asset ratio, C&I loan/asset ratio, and tier 1 ratio. Bank-county and county-year fixed effects are also controlled. Standard errors are clustered at bank level. *, **, and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	Loan size $\leq$\$100k		*Loan size* $\in$ (\$100k,\$250k)		*Loan size* $\in$(\$250k, \$1m)	
	All	Unexposed Counties	All	Unexposed Counties	All	Unexposed Counties
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Total loan amount						
Shale liquidity shock	0.001	0.011	-0.003	0.004	0.051***	0.063***
	(0.031)	(0.032)	(0.018)	(0.020)	(0.019)	(0.021)
Bank Char. t-1	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.	905,434	794,945	905,434	794,945	905,434	794,945
R^2	0.80	0.80	0.76	0.77	0.78	0.78
Panel B. Total loan number						
Shale liquidity shock	0.006	0.012	-0.002	0.001	0.011***	0.014***
	(0.031)	(0.033)	(0.005)	(0.005)	(0.004)	(0.004)
Bank Char. t-1	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.	905,434	794,945	905,434	794,945	905,434	794,945
R^2	0.88	0.88	0.87	0.87	0.87	0.88

Table 8: Bank Liquidity and Small Business Creation

This table reports the 2SLS IV regression results for the effects of local banks' average exposure to the shale liquidity shock on small business creation in the local county. Creation of small businesses, which are measured by unit of establishment based on the NETS data, are grouped by county-size-year (Columns 1-3) or county-industry-size-year (Columns 4-6). Industry is classified by the 2-digit NAICS code, and size is classified by employment size categories 1-4, 5-9, 10-19, 20-49. The dependent variable is the log number of new establishments started at period t. The key variables of interests include the CRA-lending-weighted average exposure to the shale liquidity shock across all local banks at period t, and its interaction term with the dummy indicator whether the establishment has more than 5 employees. Local county characteristics controls include lagged log population, income per capita, labor market participation, employment, ratio of proprietor employment (Columns 2, 3, 5, and 6), as well as local banks' average financial conditions (Columns 3 and 6). County-size and year fixed effects are controlled in Columns 1-3, and county-industry-size and industry-year fixed effects are controlled in Columns 4-6. Standard errors are clustered at county level. *, **, and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	Small Business Creation					
	County-Year			County-Industry-Year		
	(1)	(2)	(3)	(4)	(5)	(6)
Shale liquidity shock$_{County\text{-}Avg}$	-0.0046	-0.0048	-0.0051	0.0034**	0.0023	0.0021
	(0.0035)	(0.0034)	(0.0034)	(0.0016)	(0.0015)	(0.0015)
Shale liquidity shock$_{County\text{-}Avg}$	0.0159***	0.0158***	0.0158***	-0.0013	-0.0016	-0.0017
× Employee>=5	(0.0035)	(0.0035)	(0.0035)	(0.0016)	(0.0016)	(0.0016)
County Char. t-1		Y	Y			Y
Avg. Local BK Char. t-1			Y		Y	Y
County-Size FE	Y	Y	Y			
County-Ind-size FE				Y	Y	Y
Year FE	Y	Y	Y			
Ind-Year FE				Y	Y	Y
Obs.	117694	117694	117694	2365090	2365090	2365090
R2	0.96	0.96	0.96	0.90	0.90	0.90

Table 9: Bank Liquidity and Job Creation

This table reports the 2SLS IV regression results for the effects of local banks' average exposure to the shale liquidity shock on the expansion of existing small businesses in the local county. Small businesses, which are measured by unit of establishment based on the NETS data, are grouped by county-size-year (Columns 1-3) or county-industry-size-year (Columns 4-6). Industry is classified by the 2-digit NAICS code, and size is classified by employment size categories 1-4, 5-9, 10-19, 20-49. The dependent variable is the log change of employment between period t and t+1 for establishments that already exist in the current period t. The key variables of interests include the CRA-lending-weighted average exposure to the shale liquidity shock across all local banks at period t, and its interaction term with the dummy indicator whether the establishment has more than 5 employees. Local characteristics are controlled accordingly, including lagged terms of log population, income per capita, labor market participation, employment, ratio of proprietor employment (Columns 2, 3, 5, and 6), as well as local banks' average financial conditions (Columns 3 and 6). County-size and year fixed effects are controlled in Columns 1-3, and county-industry-size and industry-year fixed effects are controlled in Columns 4-6. Standard errors are clustered at county level. *, **, and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	Employment Growth					
	County-Year			County-Industry-Year		
	(1)	(2)	(3)	(4)	(5)	(6)
Shale liquidity shock$_{County\text{-}Avg}$	0.0002	0.0003	0.0002	0.0002	0.0001	0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Shale liquidity shock$_{County\text{-}Avg}$	0.0013***	0.0013***	0.0013***	0.0007***	0.0009***	0.0009***
× Employee>=5	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
County Char. t-1		Y	Y			Y
Avg. Local BK Char. t-1			Y		Y	Y
County-Size FE	Y	Y	Y			
County-Ind-size FE				Y	Y	Y
Year FE	Y	Y	Y			
Ind-Year FE				Y	Y	Y
Obs.	117,674	117,674	117,674	2,344,033	2,344,033	2,344,033
R2	0.23	0.23	0.23	0.19	0.19	0.19

Table 10: Bank Liquidity and Business Exit

This table reports the 2SLS IV regression results for the effects of local banks' average exposure to the shale liquidity shock on the exit small businesses in the local county. Small businesses, which are measured by unit of establishment based on the NETS data, are grouped by county-size-year (Columns 1-3) or county-industry-size-year (Columns 4-6). Industry is classified by the 2-digit NAICS code, and size is classified by employment size categories 1-4, 5-9, 10-19, 20-49. The dependent variable is the percentage share of establishments closed in a county (or county-industry) in each year. The key variables of interests include the CRA-lending-weighted average exposure to the shale liquidity shock across all local banks at period t, and its interaction term with the dummy indicator whether the establishment has more than 5 employees. Local characteristics are controlled accordingly, including lagged terms of log population, income per capita, labor market participation, employment, ratio of proprietor employment (Columns 2, 3, 5, and 6), as well as local banks' average financial conditions (Columns 3 and 6). County-size and year fixed effects are controlled in Columns 1-3, and county-industry-size and industry-year fixed effects are controlled in Columns 4-6. Standard errors are clustered at county level. *, **, and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	Small Business Exit					
	County-Year			County-Industry-Year		
	(1)	(2)	(3)	(4)	(5)	(6)
Shale liquidity shock$_{County\text{-}Avg}$	0.0079***	0.0080***	0.0081***	0.0033***	0.0033***	0.0033***
	(0.0005)	(0.0005)	(0.0005)	(0.0003)	(0.0003)	(0.0003)
Shale liquidity shock$_{County\text{-}Avg}$	-0.0106***	-0.0106***	-0.0106***	-0.0042***	-0.0042***	-0.0042***
× Employee>=5	(0.0006)	(0.0006)	(0.0006)	(0.0003)	(0.0003)	(0.0003)
County Char. t-1		Y	Y			Y
Avg. Local Bank Char. t-1			Y		Y	Y
County-Size FE	Y	Y	Y			
County-Ind-size FE				Y	Y	Y
Year FE	Y	Y	Y			
Ind-Year FE				Y	Y	Y
Obs.	117,694	117,694	117,694	2,365,090	2,365,090	2,365,090
R2	0.50	0.51	0.51	0.24	0.24	0.24

Appendix

Table A1: Robustness Test: Effects on SBA Guarantee Ratio

This table reports the robustness test results for the effects of bank exposure to the shale liquidity shock on the guarantee ratio of SBA lending (Columns 1-2) at loan level and on SBA lending amount under the Express Program, which has a fixed guarantee ratio of 50%, at bank-county-year level (Columns 3 and 5) or bank-county-industry-year level (Columns 4 and 6). All regressions control for lagged bank financial characteristics and fixed effects are controlled accordingly. Standard errors are clustered at bank level. *, **, and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

	Guarantee Ratio		New vs. Existing Businesses		Emp Size Below vs. Above 5	
	(1)	(2)	(3)	(4)	(5)	(6)
Shale liquidity shock	0.003	0.002	-0.016	-0.026	-0.048*	-0.042
	(0.003)	(0.003)	(0.030)	(0.029)	(0.027)	(0.028)
Shale liquidity shock			0.019***	0.037***		
× Existing business			(0.006)	(0.009)		
Shale liquidity shock					0.080***	0.082***
× Employee≥5					(0.009)	(0.010)
Bank Char. t-1	Y	Y	Y	Y	Y	Y
Bank-County-Type fixed effects			Y		Y	
Bank-County-Ind-Type fixed effects	Y	Y		Y		Y
County-Year fixed effects	Y		Y		Y	
County-Ind-Year fixed effects		Y		Y		Y
Obs.	386,822	386,822	57,944	129,905	60,812	134,046
R^2	0.63	0.64	0.69	0.71	0.68	0.71