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Shared Destinies? Small Banks and Small Business Consolidation *

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Abstract

The industrial and banking sectors have each seen consolidation over the past fifteen years, with small institutions representing an ever-shrinking share. Existing literature argues that small banks' comparative advantages lie in small-business finance. We argue that some of the consolidation in the banking sector is a consequence of changes to the industrial organization of the real economy. We use a Bartik instrument and variation in exposure to industries with different patterns of small-business growth to show that the real-side demand for small-business finance is partially responsible for the relative decline in the deposits, income, and loan growth at small banks. We do not find that small-business growth impacts large banks nor do we find that large-business growth affects small banks. The results are predominantly driven by the propensity of small banks to be acquired.

Keywords: consolidation, banks, relationship lending, Bartik instrument

JEL Codes: G21, G34, L25, R12

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I. Introduction

Over the past fifteen years, the role of small banks in the banking sector has declined dramatically around the United States. In 2002, the average county share of bank deposits held at banks with less than \$1 billion in assets[1] was approximately 65 percent. By 2017, the average county share of bank deposits held at small banks had fallen to about 50 percent.[2] Among the leading explanations for the consolidation of the financial services industry are regulatory changes, technological advances in lending, and changes to scale economies.[3] Given the outsized role that small banks play in small-business lending,[4] academics and policy-makers have expressed concern that the trends in the banking industry may have pernicious effects on small business and the economy. Taking as given the technological and regulatory factors that influence financial firms, existing literature examines how financial sector trends have affected small firms and economic growth.[5] In this paper, we examine to what extent the causality might run in the opposite direction. That is, to what extent have trends in the organizational structure of the real economy contributed to changes in the organizational structure of the banking industry. Understanding the direction of causality is particularly important in the context of the economic fallout of the 2020 coronavirus pandemic, the associated government response, and the implications for future financial and industrial consolidation.

Figure 1 shows the secular decline of national small-firm (<250 employees) employment shares and small-bank ($<$ \$1 billion in assets) deposit shares from 2000 through 2017.[6] Although small-firm employment shares initially rise during the time period, they fall nearly two percentage points in share going into the 2008 financial crisis. During the recession, small-

[1] All dollar values in the paper are expressed in constant 2002 dollars.

[2] The decline in the national small-bank share of deposits has been similarly large, falling from about 24 percent to just 10 percent.

[3] Although it predates the time period of interest in this study, Berger, Demsetz, and Strahan (1999) and references therein provide a nice review of leading theories on financial consolidation that continue to form the basis of much discussion.

[4] See Elyasiani and Goldberg (2004) and references therein.

[5] E.g. Cetorelli and Strahan (2006), Sapienza (2002)

[6] Some county data is not available in 2000 (including for some entire states). We fix the set of counties to the 2000 sample for construction of national data throughout the paper to ensure that trends are not driven by changes in reporting counties. From this, some entire states are excluded.

firm employment shares increased slightly before continuing on a downward trend from 2011 through 2017. Meanwhile, small-bank deposit shares have seen continual decline from 2000 through 2017, falling by approximately fourteen percentage points.

Our paper rests on two distinct observations from the literature. The first is that small banks' comparative advantages lie in their services to small businesses.[7] The second is that, at least in part, shocks to the real economy have resulted in the loss of small businesses and a change in the organizational structure of industry. From that premise, shocks to the real economy that induce a (relative) reduction in small businesses are expected to induce a reduction in demand for financial services from those firms. If small banks disproportionately serve the negatively impacted small firms, then small banks will disproportionately be affected. For example, advances in inventory management and vertical supply chains may contribute to the success of big box retailers' abilities to exploit economies of densities, whose expansion comes at the expense of small local retailers.[8] To the extent that national retailers access credit through large banks or capital markets and local retailers seek credit from local financial institutions, we would expect these technological changes to lead to a decrease in the demand for small-bank financial services. Similarly in agriculture, the Kansas City Federal Reserve Bank Ag Finance Databook reports in July 2018, "the size of livestock loans also has been trending higher, suggesting that consolidation has contributed to fewer, larger farms with larger lending needs." The Kansas City Federal Reserve Ten Magazine November 2017 edition ponders "does farm expansion make owners think the small community bank can no longer provide them the amount of credit and services they need?"

The empirical challenge to assess the impact of small firm outcomes on small bank outcomes is that theory and existing evidence in the literature suggest that small bank outcomes affect small firm outcomes. We expect that known technological and regulatory changes affecting small banks reduce the small-bank supply of financial services to their customers, who are disproportionately small firms. Stated differently, this paper aims to evaluate the effects of the

[7] There is no single definition of small businesses in the literature. The basis for definitions include firm employees (Petersen and Rajan (2002)), sales (Sapienza (2002)), and loan size Avery and Samolyk (2004)).

[8] See, Holmes (2011) and Jia (2008).

demand for small-bank financial services on small-bank outcomes, which must be disentangled from small-banks' *supply* of financial services. To resolve this challenge empirically, we rely on a Bartik instrument. In our primary specification, we construct a county-year level Bartik instrument using annual national industry growth by firm size[9] from 2003 through 2017 (such that 2003 reflects 2002-2003 growth) weighted by year 2000 county industry shares. The Bartik instrument relies on ex-ante variation in industry shares and the identification assumption for the purposes of this paper is that this variation does not predict innovations to small-bank financial services supply, given the other controls. We discuss this assumption and associated diagnostic tests suggested by Goldsmith-Pinkham, Sorkin, and Swift (2019) in Section VI.

We find that changes in small-firm employment are statistically and economically significant factors to changes in small-bank deposits. Across specifications, we find that a one percentage point decrease in small-firm employment is associated with approximately a 0.9 percentage point decrease in small-bank deposits. This coefficient implies that a one standard deviation increase in county-year small-firm employment growth (7.2 percentage points) is associated with a 6.5 percentage point increase in small-bank deposit growth, or 0.28 standard deviations. In contrast, we find that large-firm employment has no statistically or economically significant relationship with small-bank deposits after controlling for small-firm employment growth.

We then construct proxies for county-level small-bank balance sheet and income variables by apportioning small-bank financial statements to counties based upon their deposit footprint. Using the Bartik instrument, we find that small-firm employment growth is positively associated with increased small-bank small-business lending, and commercial and industrial loan growth, but less so related to residential real estate loan growth. Furthermore, we find that small-firm employment growth is positively associated with small-bank return on assets and that this effect emanates predominantly through lower loan loss provisions.

Given our baseline results, we test for heterogeneous effects. We find that the magnitude of the effects are decreasing in the urbanization of the county. Relative to rural areas, the

[9] Unless otherwise specified, we use log differences +1 interchangeably with growth through the rest of the paper.

effect of small-firm employment growth on small-bank deposit growth is twice as high in micropolitan counties and more than three times as large in urban counties. This is consistent with evidence that urbanization is associated with larger declines in small-bank deposit shares over the past fifteen years. We also examine heterogeneous effects by the competitiveness of the banking industry. We find that the effect of small-firm employment on small-bank deposits is approximately twice as high for the most concentrated tercile of counties (as measured by the Herfindahl-Hirschman Index, HHI) relative to the middle and bottom terciles.

We then examine the mechanisms through which small-bank deposits are affected by changes to small-firm employment. In particular, we examine the relationship between small-firm employment growth and the propensity of small banks to be acquired, to grow through acquisition, and to fail. Our findings demonstrate that our main results are driven by the propensity of small banks to be acquired in the face of declines of small-firm employment (or, in contrast, a lesser propensity to be acquired in the presence of small-firm employment growth). We do not find that small banks are more likely to acquire other banks or fail as a result of changes to small-firm employment growth. Our results are consistent with the view that small banks specialize in lending to small businesses and that in the absence of small-business financial service demand, economies-of-scale from a larger bank model may be more profitable than a small-bank business model.

This paper relates to strands of literature on bank consolidation, industrial sector consolidation, and relationship banking. The literature on bank consolidation is extensive and well-established. Berger, Demsetz, and Strahan (1999) provide a summary of the literature, highlighting leading theories of consolidation through the time of publication. Among the leading explanations the authors present are increased economies-of-scale from technological innovation, international consolidation of markets, and deregulation. Radecki, Wenninger, and Orlow (1997) argue that alternative delivery of deposit services (e.g. ATMs) may improve economies of scale. Similarly, Petersen and Rajan (2002) and Berger and Frame (2007) discuss developments in small-business credit scoring and the associated economies-of-scale. Arguments that bank consolidation is a consequence of deregulation follow from major legislation passed in the 1990s that removed barriers to bank size. Among the barriers lifted by legislation were laws limiting interstate bank branches (Riegle Neale Act of 1994) and prohibitions on affiliations with certain nonbank financial intermediaries (Gramm-Leach-Bliley Act of 1999). Consistent with this theory, Jayaratne and Strahan (1998) show that removal of interstate restrictions on branching increased bank merger and acquisitions. More recently, Cyree (2016) argues that post-crisis financial regulation is associated with fixed compliance costs that further increase economies-of-scale and limit the profitability of small banks. Such an argument was, at least in part, the rationale behind the passage of the Economic Growth, Regulatory Relief and Consumer Protection Act of 2018.[10]

Both theoretical and empirical literature examine real-side consolidation. Goldmanis, Hortascu, Syverson, and Emre (2010) show that e-commerce contributes to decreased profitability of small firms. Jia (2008) finds that Walmart entry is responsible for approximately 50 percent of the nationwide decline in small discount retailers. More generally, Grullon, Larkin, and Michaely (2019) look at publicly traded firms in Compustat and find that large firm shares and market concentration have generally increased across industries, with "surges" in various measures of consolidation and concentration beginning in the late 1990s or early 2000s. They find that market share for the largest four firms increased in more than 80 percent of industries and that for 21 of 65 industries, the largest four firms' collective market share increased by more than 40 percentage points. Similarly, Council of Economic Advisers (2016) and citations therein document declining competition across industries. The report notes that a "natural question is whether increased concentration in one area of the supply chain leads to increased concentration in other parts of the supply chain." In related papers, Crawford and Yurukoglu (2012) and Gowrisankaran, Nevo, and Town (2015) examine the downstream effects of consolidation of television and managed care industries, respectively. Most similar to this paper is Allen (2019) who, in an analysis developed in parallel with ours, uses Walmart expansion as an instrument on small-business retail. Despite different time periods and identification as-

[10]See Crapo (R-Idaho), Chairman of the U.S. Senate Committee on Banking, Housing and Urban Affairs remarks on October 2, 2018.

sumptions, both our paper and his paper find evidence that real-sector industrial organization trends have played a role in the consolidation of the banking industry.

Underpinning the narrative of this paper is the literature on small ("community") banks and their comparative advantage in relationship lending. Relationship banking is defined as financial services that invest in customer-specific information, with the profitability of investments evaluated across repeated customer interactions (Boot (1999)). Berger et al. (2005) and Chakraborty and Hu (2006) argue that the proprietary information gained through relationship banking gives community banks a distinct comparative advantage over their large-bank competitors. Consistent with the view that community banks have a comparative advantage in relationship lending, Carter and McNulty (2005) find that community banks outperform their peers in the more informationally opaque small business lending market. Community banks' comparative informational advantage in small business and relationship lending may emanate, in part, from their distinct knowledge of local markets. Through their abilities to acquire "soft" information, community banks expand access to credit. The organizational structure typically exhibited within community banks may provide them advantages in relationship lending compared to larger banks. Career paths for loan officers at community banks and larger banks differ, with the larger banks offering more intrafirm location and position mobility. As a result, loan officers at community banks may have more incentive to create long-term lending relationships (Berger and Udell (2002), Petersen and Rajan (1995)). Agency frictions between loan officers and management may also be mitigated through the flat organizational structure of community banks, as the close proximity of senior management and the loan office reduces intrafirm monitoring costs. Stein (2002) contends that a flat organizational structure is better than a hierarchical structure at producing "soft" information, while large hierarchies perform better when information can be "hardened." Recognizing that the comparative advantage is neither static (Berger, Cowan, and Frame (2011)) nor uniform across the industry (Federal Deposit Insurance Corporation (2018)), we rely on the view from the relationship lending literature that small banks have a comparative advantage in serving small business customers relative to other financial institutions.

The rest of the paper is organized as follows. Section II discusses the data used in the analysis. Section III discusses the Bartik methodology and the diagnostic tests performed (and to be performed) to assess the validity of the instrument. Section IV discusses the results. Section V discusses how our small business employment measure relates to measures of small business lending. Section VI unpacks the Bartik instrument to gain a better understanding of the implicit identification assumptions in our estimator. Section VII concludes.

II. Data

Our paper assumes that small banks have a comparative advantage in serving small businesses and, consequently, that shocks to small businesses disproportionately affect small banks. Primarily, the narrative and the literature focus on this comparative advantage as emanating through small business lending. While this forms the basis of our hypothesis, small-business performance might also affect small-bank growth through other banking services, including small-business deposits (Kennickell, Kwast, and Pogach (2015)) or lending to households (e.g. home equity line of credit) whose ultimate purpose is to support a small business (see Robb and Robinson (2014) and Avery, Bostic, and Samolyk (1998)).

To measure small businesses, we use Census Quarterly Workforce Indicators (QWI) data on firm employment.[11] QWI provide local labor market statistics by industry and are sourced from the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee microdata. LEHD covers over 95 percent of U.S. private sector jobs and is itself sourced from administrative records on employment. For this paper, the critical information provided by the employer based records is the number of employees in a county by the size of the firm. Note that we use firm size, rather than establishment (physical place of work) size because our narrative revolves around the premise that the banking decisions are made at a firm, rather than an establishment, level. For example, as of January 2017, Target Corporation

[11] In Section V, we show that county level small firm employment growth is strongly correlated with small business loan growth, as measured in Community Reinvestment Act (CRA) data. However, CRA data does not include banks below the $1 billion threshold and is therefore not a viable source of data for small bank loan supply for this study.

had 323,000 employees and 1,803 stores, approximately 180 employees per store.[12] We view the relevant measure for Target with regard to its choice of financial services to be 323,000, not 180. Thus, we want our measure of local firm employment for a county with a single Target store to assign 180 employees to a firm of size 323,000 employees, consistent with the measurement in QWI. QWI includes data on the number of employees by industry by five different firm sizes: 0-19 employees, 20-49 employees, 50-249 employees, 250-499 employees, and 500+ employees. Through the rest of the paper, we use these size categories to define small (<250) and large firms (>500), designating firms with 250 to 499 employees as neither small nor large.[13] We use June data from each year for all specifications to align with the timing of the branch data, discussed below.

In Figure 2, we plot industry employment growth and changes in small-firm employment shares by industry (plots normalized to 0 in year 2000). First, we note that there is considerable variation across industries in growth rates, changes in small-firm employment shares, and the relationship between the two. For example, the retail industry (44-45) saw virtually no cumulative growth in employment between 2000 and 2017. However, small retail-firm employment shares fell by nearly ten percentage points over the period, the largest decline in small-firm employment shares of any industry. Manufacturing (NAICS 31-33), which experienced one of the largest employment declines during the period, saw a slight increase in small-firm employment shares. Meanwhile, the industry with the largest increase in small-firm employment share, Mining (NAICS 21), also had an increase in overall employment.

For bank data, we primarily use Summary of Deposits (SOD) data from the Federal Deposit Insurance Corporation (FDIC). SOD include bank branch location and branch deposits. The data are collected for all FDIC-insured institutions, which includes thrifts, but does not include credit unions. The data is collected annually as of June 30. The reporting allows for consolidation of deposit accounts across offices, but only within a county. For this paper, we aggregate deposits to the county level by bank when computing measures of competition and

[12] Target Corporation, 2016 Annual Report.

[13] We use 250 as the benchmark for small firms rather than 500 to avoid a mechanical relationship between small-firm shares and large-firm shares.

across all branches in a county by size for computing large- and small-bank deposit and branch growth and shares. We also rely upon Reports of Condition and Income (Call Reports) to measure bank level variables, most importantly assets. For most of the analysis, we define banks as "small" if they have less than $1 billion (2002 dollars) in assets and "large" if they have more than $50 billion. The $1 billion cutoff for small banks is common in the literature[14]. Meanwhile, the $50 billion definition for large is consistent with the Dodd-Frank Act's original threshold for enhanced prudential standards. In addition, we apportion small bank financial statements into counties based upon the bank's county deposit shares and aggregate across banks to obtain a proxy for aggregate small-bank income and balance sheet measures (discussed in further detail below).[15]

In Figure 3 we plot average national changes in the small-firm employment shares and small-bank deposit shares across counties. The time series plots suggest that there is a strong temporal correlation between small-firm employment shares and small-bank deposit shares. Small bank and small firm shares both tended to decline from 2000 to 2017, though declines for both were steepest in the boom leading up to the 2008 financial crisis and the post-crisis recovery. Declines were the smallest (even increasing in some years) for small firms and small banks at the tail end of the 2001 recession and during the Great Recession.

We report summary statistics in Table I for the main sample period 2003 to 2017. The annual average decline of small-bank deposit shares across counties is 62 bps, while the average decline in small-firm employment share across counties is nearly 19 bps. In the case of banks, we find that the decline of small bank share is entirely accounted for by the rise in large-bank deposit share (which is not mechanical, given that banks between $1 billion and $50 billion are included in neither definition). In the case of real businesses, approximately 80 percent of the decrease in small firm employment share is accounted for from an increase in large firm share (15 bps). Changes in small-firm employment and small-bank deposit shares can also be observed through log differences (growth). Average annual growth for large firms across

[14]For example, Berger et al. (2005).

[15]See Section IV for more details.

county-years is approximately 106 bps during this period, though only about 8 bps for small firms. Meanwhile, small bank deposits grew by 120 percent and small bank branches shrunk by 160 bps during the sample period. In contrast, large bank deposits grew on average by 1442 bps across county-years and large bank branches grew by 224 bps. Collectively, both the real and banking industries saw stagnant growth if not declines in smaller institutions and considerable growth in larger institutions from 2003 to 2017.

We also report summary statistics for the county-proxies for small-bank financial variables in Table I.[16] Average small-bank return on assets is approximately 120 bps during our sample period and return on equity is 1139 bps. County average small-bank small-business lending growth declined on average by 109 bps, though commercial and industrial loans and residential real estate lending grew by 59 bps and 111 bps, respectively.[17] Regarding mergers, we report the proportion of deposits in a county-year associated with the small banks that are acquired, act as an acquirer, or fail. Approximately 1.51 percent of deposits in a county-year are associated with a small bank that is acquired, 1.85 percent of deposits in a county-year are associated with a small bank that acquires another bank, and 0.18 percent of deposits are associated with a small bank that fails in a county-year. We further discuss the summary statistics on mergers in Section IV.E.

In Table II we present five year growth statistics for our variables of interest to show how the trends from Table I differ across the pre-crisis, crisis, and post-crisis periods. Across each of the five year periods, small-firm employment and small-bank deposit shares fell, though the

[16]Note that the sample size is somewhat smaller for these variables as we cannot calculate return on assets for counties without a small-bank presences. We also require that small banks are defined as "small" in both the year of measurement and the prior year for the purposes of defining average bank assets. We also exclude 0.6 percent of observations where log differences in loan volumes are greater than 2, corresponding to about 650 percent growth. Results are robust to alternative restrictions on outliers.

[17]We use growth in small loans for commercial and industrial purposes plus small agricultural loans as a proxy for small business loan growth. Our results are robust to various definitions of small business loans. The results are strongest using only small loans for commercial and industrial purposes. The results are also similar, though slightly weaker, when including small nonfarm nonresidential real estate loans and/or agricultural loans backed by real estate. Although commonly used in the literature all definitions of small-business lending from the Call Reports are limited in that they do not measure loans to small businesses per se, but rather small loans to businesses, independent of firm size. Goldston and Lee (2020) argue that this results in an industry-wide understatement of small-business lending, but that the Call Report measure only "mildly understates" small-business lending for our definition of small banks.

dynamics differed across periods. Prior to the financial crisis, the average county saw growth in both small-bank deposits (9.8 percent) and small-firm employment (4.9 percent). However, both saw their relative shares decline as larger institutions grew even faster, with (180 percent for large-bank deposits and 6.6 percent for large-firm employment). These trends led to average declines in small-bank deposit shares of 3.0 percent and small-firm employment share of 0.32 percent across counties. During the five-year period encompassing the 2008 financial crisis and associated recession period (June 2007 through June 2012), the average county saw an absolute decline in both small-bank deposits (13.1 percent) and small-firm employment (6.1 percent). In both cases, large-firm employment growth (0.28 percent) and large-bank deposit growth (44.4 percent) continued, albeit at slower rates than in the expansion period. In the recovery period (June 2012 to June 2017), small firms continued to lose employment share (1.53 percent), driven by large-firm employment growth outpacing small-firm employment growth (9.0 percent to 2.0 percent), similar to the pre-crisis period. For banks in the recovery period, the average county saw declines in small-bank deposit share as small-bank deposits shrunk at a faster rate than they did for large banks (23.1 and 5.0 percent, respectively).

In Figures 4 and 5 we map the county trends in small-firm employment growth and small-bank deposit growth, respectively. Starting with Figure 4, we show that county level small-firm employment grew the 2002 to 2017 most in the Mountain Region (e.g. CO, UT, NV) with strong growth in counties across southern Texas and western North Dakota. Areas in Appalachia, the Midwest, and the Plains also appear to generally have lower small-firm employment growth compared to the rest of the country, despite reasonably strong small-firm employment growth in the urban areas in these regions (e.g. Indianapolis, Columbus, Pittsburgh). In Figure 5, we map small-bank deposit growth across counties in the United States from 2002 to 2017. In some areas, small-bank deposit growth resembles that of small-firm employment growth. Texas and Western North Dakota have notably strong small bank deposit growth, while Appalachia generally has weaker small-bank deposit growth. However, small-bank deposit growth and small-firm employment growth have notable differences in the Heartland and rural versus urban areas. Whereas small-business employment growth seems weakest in the Heartland and rural areas, this is where small-bank deposit growth is strongest.

In Table III we show that the correlations suggested Figures 4 and 5 are borne out statistically. In Column 1 we show results from a univariate regression of small-bank deposit growth on small-firm employment growth for 2003 through 2017 and find a statistically significant relationship at the 1 percent level. The coefficient of 0.09 implies that a 1 percent growth in county small firm employment is associated with a 9 bps increase in county small bank deposit growth.[18] In Column 2 we show that the result is similar in magnitude and significance when including county level controls from 2000, including log population, unemployment rate, an urban indicator variable, log income per capital, log number of branches and the small bank deposit share. Of the controls, only log population and small bank deposit share are statistically significant, with larger counties by population associated with slower deposit growth and counties with more small bank deposit share associated with lower small bank deposit growth. In Column 3 we similar show that the association persists at a similar magnitude and significance when adding county fixed effects.[19] In Columns 4 through 6 we run a similar analysis but use large-firm employment growth rather than small firm employment growth as an explanatory variable. In none of the specifications is large-firm employment growth statistically or economically significant in its association with small-bank deposit growth. In Column 7, we show that small-firm employment growth remains a statistically strong predictor of small-bank deposit growth after controlling for large-firm employment growth allowing for county fixed effects. In Column 8, we show that small-firm employment remains a strong predictor of small-bank deposit growth after allowing for contemporaneous macroeconomic controls, namely, county population growth and county income per capita growth.

[18] All standard errors are clustered at the state level unless noted otherwise. We also drop outliers in which log change small bank deposits is greater than 5 (corresponding to growth rates larger than ten thousand percent). This eliminates approximately 0.7 percent of observations. The results are robust to alternative definitions of outliers.

[19] We do not have year 2000 controls for all counties, so the count is slightly larger when we use county fixed effects, our preferred specification.

III. Methodology

We use a Bartik-like approach to estimate the effect of small-firm performance on small-bank performance. We are interested in the following equation:

$$y_{ct} = \rho D_{ct} + x_{ct}\beta_0 + \epsilon_{it} \tag{1}$$

where c are counties, t is year, y_{ct} are bank outcomes, D_{ct} is a vector of controls, x_{ct} are real sector outcomes, and ϵ_{ct} is a structural error term. In our primary analysis, we are interested in small-bank deposit log differences as the y_{ct} variable and real small-firm employment log differences as the x_{ct} variable. The identification challenge from the above equation is that small-firm outcomes may be driven by small-bank outcomes, rather than the reverse, which biases the OLS parameter estimate of β_0. Indeed, established literature (e.g. Cetorelli and Strahan (2006)) suggests that shocks to small bank operations (e.g. mergers) affect small businesses.

The Bartik instrument is constructed by taking the inner product of county-specific industry shares and national real industry-period growth rates (for the variable of interest).[20] As discussed in Goldsmith-Pinkham, Sorkin, and Swift (2019), the underlying assumption from this approach is that the industry shares are exogenous (conditional on the controls) to innovations in the outcome variable (e.g. small-bank deposit growth). Namely, the Bartik instrument is constructed as:

$$B_{ct} = Z_{c0}G_t = \sum_k z_{ck0}g_{kt} \tag{2}$$

where G_t is a $1 \times K$ vector of national real (i.e. non-finance) industry small business growth

[20]Due to disclosure rules, some county-industries report missing rather than zeros when the values are small. To maintain a larger sample of counties, we set censored county-industry employment numbers to zero rather than missing. In unreported analysis, we exclude counties with any missing industry employment values and find similar results.

rates in year t, Z_{c0} is a $1 \times K$ vector of initial (year 2000) industry shares for county c. This produces a standard two-stage least squares estimation, where the first stage regresses the explanatory variable of interest (county c small firm growth in period t) on the controls and the Bartik instrument:

$$x_{ct} = D_{ct}\tau + B_{ct}\gamma + \eta_{ct}. \tag{3}$$

For control variables D_{ct} we generally use county fixed effects and time fixed effects, though in some specifications use year 2000 county controls, namely: log population, log income per capital, an urban indicator variable, log bank branches, and small bank deposit share. We assume that these variables are strictly exogenous for this methodology and therefore prefer specifications with county fixed effects.

In Table IV we report regressions of small-firm employment growth on the Bartik instrument. First, in Column 1 we report the relationship between the instrumented variable, small-firm employment growth, and the controls. Small firm employment growth has strong positive correlations with a number of control variables. Small firm growth is positively correlated with 2000 values of log county population, an urban indicator, and log income per capita and negatively correlated with 2000 values of unemployment and log bank branches. In Column 2 we report the results of a regression of small firm employment growth on the Bartik instrument, with year fixed effects and the year 2000 controls. The coefficient on the Bartik instrument is approximately 1, with a F-statistic of 57. Results are similar when we include county fixed effects in Column 3. In Columns 4, 5, and 6 we report regression results of small firm employment on the Bartik instrument for the separate five year samples 2003-2007, 2008-2012, and 2013-2017 (all years inclusive). In each case, the F-statistics for the associated regressions are 3.8, 29.2, and 7.0, respectively. In Columns 7 and 8 we report first-stage regressions of large-firm employment growth on a Bartik instrument that uses national large-firm employment industry trends. Using both year 2000 controls (Column 7) and county fixed effects (Column 8), the large-firm Bartik instrument is a strong predictor of large-firm employment with a first-stage coefficient of approximately 1.5 and an F-statistic greater than 50. Thus, the instrument is strong under Stock and Yogo (2005), though not for each of the subsample periods.

IV. Results

A. Deposits

In Table V we report the results of our main specification of small bank deposit growth on instrumented small firm employment growth. In Column 1, we report the results of an OLS regression of small bank deposit growth on the Bartik instrument. The coefficient on the Bartik instrument is 0.87 and statistically significant at the one percentage point level.[21] The result suggests that a one percentage point increase in annual county small firm employment growth is associated with 0.87 percentage point increase in county small bank deposit growth. Similarly, in Column 2, we find that county small-firm employment growth as measured with the Bartik instrument is associated with a 1.06 percentage point increase in small bank deposit growth using county fixed effects, again significant at the one percent threshold. In Column 3, we report results of a two stage least squares regression of small-bank deposit growth on small-firm employment growth and year 2000 controls. Similar to Column 1 using the Bartik instrument and OLS, the parameter estimate is approximately 0.87. In Column 4, using two stage least squares with year 2000 controls and year 2000 population weights, we find that a one percentage point increase in small-firm employment growth is associated with a 1.5 increase in small-bank deposit growth. In Column 5, we report results from a two-stage least squares specification with county fixed effects, which we refer to as our baseline specification. We find that a one percentage point increase in small-firm employment is associated with a 0.91 percentage point increase in small-bank deposit growth, significant at the one percent level. In Column 6, we show that the result is robust to the addition of (endogenous) contemporaneous

[21] We note that the order of magnitude in the coefficients is much higher using the Bartik instrument than in the OLS specifications. We address this in Table VI.

county macroeconomic controls (log differences in population and income per capita growth). Thus, the relationship between small-firm employment growth and small-bank deposit growth does not seem to be simply a function of broader county economic conditions.

While Columns 1 through 6 show a robust relationship between small-firm employment and small-bank deposits, it is unclear whether small-firm employment is unique in this regard. In Columns 7 and 8, we show using a two-stage least squares approach with year 2000 controls and county fixed effects, respectively, that there is a statistical relationship between small-bank deposits and large-firm employment growth, albeit at half the magnitude as the relationship between small-bank deposits and small-firm deposits. In Columns 9 and 10, we report results from a two-stage least squares regression with both the large-firm and small-firm employment growth, using Bartik instruments separately constructed for large-firm and small-firm national industry employment growth. We find that the effects of employment growth on small-bank deposits are driven specifically by small-firm employment growth (coefficients of 1.1 and 1.0, respectively, both significant at the one percent level) with no statistical relationship between small-bank deposit growth and large-firm employment growth.[22]

Notably, the difference between the OLS estimate in our preferred specification with county fixed effects and the two-stage least squares specification differ by an order of magnitude (0.09 versus 0.91). Given the high F-statistic for the first-stage regression, the discrepancy suggests that the outcome variable is correlated with the instrument through factors other than annual changes in log small-firm employment. We hypothesize that this may be due to the fact that the instrument may pick up national industry trends on small-firm employment in a way that the variable of interest (county-level small-firm employment) does not. In particular, our main specifications examine contemporaneous annual relationships between small-firm employment growth and small-bank deposit growth. Thus, we implicitly assume in our OLS specifications that small-firm employment growth does not affect future small-bank deposit growth. In our two-stage least squares we similarly assume that local small-firm employment growth is not affected by past national industry trends in small-firm employment. However, one might

[22] A Sargan-Hansen test fails to reject the hypothesis that the over-identifying are valid (p-value 0.29).

expect the relationships of bank variables to firm variables and firm variables to national trends to be not only within a June to June calendar year, but across years. If our variable of interest (small-firm employment) and our instrument exhibit different patterns over time, this may contribute to the discrepancy between the OLS and two-stage results.

In Table VI, we assess whether differences in serial correlation may be contributing to the differences in the OLS and two-stage estimates. In Column 1, we report regression results of annual small-firm employment growth on the instrument, including four years of lags.[23] We find that annual small-firm growth is indeed correlated with lags of the instrument. That is, national industry small-firm employment trends weighted by county industry shares correlate with local small-firm employment both contemporaneously and with lags. In Column 2, we find that local small-firm employment growth exhibits negative autocorrelation (autoregressive coefficient of -0.19). In contrast, in Column 3, we show that the Bartik instrument exhibits positive autocorrelation (autoregressive coefficient of 0.14). Thus, while OLS regressions using only the contemporaneous small-firm employment growth measure picks up a negative correlation with past small-firm employment, the contemporaneous instrument picks up the positive correlation with lags of the instrument.

As an alternative approach, we collapse our data into a panel of three five-year windows of analysis (2002-2007, 2007-2012, 2012-2017), which we label a pre-crisis, a crisis and recession, and a recovery period, and calculate the cumulative five-year growth rates for each variable. While, the longer horizon is also more consistent with the time-frames used in other studies using the Bartik instrument (e.g. Autor, Dorn, and Hanson (2013)), it reduces the amount of data used for analysis. In Columns 4 through 6 of Table VI, we report results from OLS regressions of five-year small-bank deposit growth on five-year small-firm employment growth. Column 4 uses year 2000 controls, Column 5 uses county fixed effects, and Column 6 uses county fixed effects with a control for large-firm employment growth. The OLS coefficients are an order of magnitude higher than those reported in Table III. This is consistent with the annual OLS coefficient on small-firm employment growth being downward biased through its

[23]In unreported analysis, we test longer lags, which are not significant.

negative autocorrelation. In Column 7, we show that the Bartik instrument using five-year national industry trends acts as a strong instrument for five-year county small-firm employment growth (F-statistic 52). In Column 8, we show that the two-stage least squares using the five-year windows produces an estimate of 0.55, significant at the five percent level. In contrast to estimations using annual data, the two-stage least squares estimate with the five-year windows is more in line with the OLS specification in Column 5. However, the estimate of 0.55 using a five-year window is somewhat below the estimate in our baseline regressions (0.91), even if not statistically different.

B. *Small-Bank Balance Sheets*

While the Summary of Deposits allows for measurement of small-bank deposits, it is also of interest to understand how small-firm employment affects bank financial and balance sheets. However, there is not data by bank-county that allows for direct measurement. Consequently, we proxy small-bank variables in the following way.[24] For each financial variable of interest w_{it} (e.g. net income, commercial and industrial loans) for bank i at time t, we apportion the bank variable into county c according to the share of the bank deposits held in the county. That is:

$$w_{ict} = w_{it} \frac{dep_{ict}}{dep_{it}},$$

where dep_{ict} are bank i deposits in county c at time t. We then aggregate small-bank financial variables across for county c in time t to obtain a small-bank county aggregate:

$$W_{ct} = \sum_{i \in c} w_{ict}.$$

In Table VII we report results from OLS regressions and the baseline two-stage least squares regressions with county fixed effects using the county proxies for aggregate small-bank lending. In Columns 1 through 3, we use log differences in small-bank small agricultural loans

[24]Note that we remain consistent with the SOD timing and use data as of June. For flow variables, this requires a four quarter lagged summation.

plus small commercial and industrial loans (often used as a proxy for small-business loans) as the independent variable, in Columns 4 through 6 we use log differences in total commercial and industrial loans, and in Columns 7 through 9 we use log differences in residential real estate loans. Columns 1 shows that small commercial and agricultural loan growth at small banks is strongly related to small-firm employment growth. Column 2 shows that small commercial and agricultural loan growth remains related to small-firm employment growth after controlling for large-firm employment growth, to which is not statistically related. Column 3 shows in a two-stage regression that small-firm employment growth is associated with an increase in small commercial and agricultural loans at small banks, significant at the one percent level. Similarly, Columns 4 through 6 show that small-firm employment, but not large-firm employment, is related to small-bank commercial and industrial loans. In addition, Column 6 shows that much of the increase in small-bank commercial loans from increased small-firm employment can be accounted for by small loan (0.83 of 0.93). For all specifications in Column 1 through 6, the parameter estimates on small-bank loan growth resemble those of similar specifications of small bank deposit growth reported in Table V. Columns 7 and 8 show a weak statistical relationship between small-firm employment growth and small-bank residential real estate lending in OLS regressions. Column 9 reports a strong statistical relationship between small-firm employment growth and residential real estate lending growth, though the coefficient is about two thirds that of the coefficient from Column 6. This is consistent with the view that small businesses use personal finances, including their home equity, as a source of funding (as in Robb and Robinson (2014)).

In Table VIII, we report results from OLS regressions and the baseline two-stage least squares regressions with county fixed effects using the county proxies for small-bank income statement variables. In Columns 1 through 3 we use county small-bank net income divided by county small-bank average assets as the independent variable, in Columns 4 through 6 we use county small-bank net income divided by county small-bank average equity as the independent variable, and in Columns 7 through 9 we use county small-bank loan loss provisions divided by county small-bank average assets as the independent variable. In Columns 1 and 2, we show that small-firm employment is strongly related to small-bank county return on assets. Column 2 demonstrates that large-firm employment growth is also strong correlated with small-bank return on assets, albeit an order of magnitude less than small-firm employment growth. In Column 3, we show in a two-stage least squares approach with the Bartik instrument that small-firm employment is associated with return on assets, significant at the one percent level. The coefficient of 0.024 in Column 3 implies that a one standard deviation increase in small-firm employment growth (7.2 percent) is associated with approximately an 18 bps increase in small-bank return on assets, equal to about 14 percent of average small-bank return on assets (or a 0.12 standard deviation increase in small-bank return on assets). In Columns 4 through 6, we run similar specifications to Columns 1 through 3, using return on equity rather than return on assets. The results are qualitatively similar to the return on assets specifications, though large-firm employment growth is only marginally significant in Column 5. In Columns 7 through 9, we show that the results from the other columns are largely driven by loan loss provisioning. Columns 7 and 8 show that small-firm employment growth is associated with decreased loan loss provisions (of similar magnitude to the increase return on assets). Column 8 shows that large-firm employment is statistically related to provisions as a fraction of assets, though at a lower order of magnitude than small-firm employment. In Column 9, we find that a one standard deviation increase in small-firm employment growth leads to a 9.5 bps reduction in loan loss provisions to bank assets, equal to approximately 22 percent of the mean loan loss provisions to assets, or a 0.13 standard deviation decrease in loan loss provisions to assets.

C. Heterogeneous Effects and Placebo Tests

C.1. Subsample Periods

In this section, we explore heterogeneous effects of our baseline regressions of small-bank deposit growth on small-firm employment growth. First, we consider heterogeneous effects across three five-year time periods and report results in Table IX. Columns 1 and 2 report estimates from 2003 to 2007 inclusive, Columns 3 and 4 report results from 2008 to 2012, and Columns 5 and 6 report results from 2013 to 2017. In each case, we report results using both an OLS specification of small-bank deposit growth on the Bartik instrument and a two-stage specification where the Bartik instruments for small-firm employment growth. We find that the parameter estimates are largest in magnitude during the 2003 to 2007 period and similar between the 2008 to 2012 and 2013 to 2017 periods. However, the parameter estimates are not statistically different across the subsample periods and are statistically weakest in the 2003 to 2007 period. Thus, it does not appear that the results are predominantly driven by any particular period in the data.

C.2. Heterogeneous Effects Across Geographies

We also explore heterogeneous effects in our baseline regressions across urbanization and across bank competition and report results in Table X. In Column 1 through 3 we examine heterogeneous effects by separating the sample into urban, micropolitan, and rural counties, respectively, based upon year 2000 classifications. We find that the effect of small-firm employment on small-bank deposits is larger for more urbanized counties in the country. These results are consistent with the observation that although small-bank presence has declined nationwide over the sample period, the effect is most pronounced in more urbanized regions of the country (see Federal Deposit Insurance Corporation (2013)). In Columns 4 through 6 we examine heterogeneous effects across counties by the level of deposit competitions, measured using HHI. For each year we assign counties to an HHI tercile and report results for the highest HHI (least competitive) tercile in Column 4, middle tercile in Column 5, and bottom tercile in Column 6. We find that the parameter estimates of the effect of small-firm employment growth on small-bank deposit growth are nearly twice as large for those counties with the least competition relative to the middle and bottom terciles. We find this result plausible, as small banks facing the least competition are most likely to be affected by real-side business growth.

D. *Alternative Specifications*

Our analysis rests on the hypothesis that small-banks' comparative advantages lie in their ability to meet the needs of small business customers. Phrased differently, large banks have a higher opportunity cost to serving small-business customers. Thus, we expect that small-firm employment growth will have smaller effects on large-bank deposit growth than it does for small-banks. In Table XI, we examine the relationship between log differences in large bank (defined as $50 billion in constant dollars) deposits and small-firm employment growth. In Column 1 we report results from OLS regressions and find no statistical relationship between small-firm employment growth and large-bank deposit growth. In Column 2 we report results from a two-stage least squares regression, using the Bartik instrument constructed with county exposures to national small-firm industry growth. Again, we find no statistical relationship between large-bank deposit growth and small-firm employment growth. In both the OLS and two-stage least squares specifications, the magnitude of the coefficients for the log differences in small-firm employment growth are an order of magnitude lower than those for similar specifications using log differences in small-bank deposits.

This paper is primarily motivated by the decreasing share of small-banks and the consolidation of the banking industry. A distinct, but related, concept surrounds bank competition. Although often used interchangeably, for the purposes of this paper, the distinction is important. We define "consolidation" as the agglomeration of smaller firms into larger firms and measure the concept in this paper by measuring small (or conversely, large) market shares. In contrast, we use the term "concentration" to refer to the competitiveness of a particular market. Following the literature, when discussed in this paper we use HHI as a market concentration measure. While consolidation and concentration are clearly related concepts, they may exhibit materially different properties because HHI is defined for a given geographical market, while firm size is defined independent of the geographical market. For this paper, this distinction is important because our question revolves around the definition of *which* banks are competitive in an area given trends in the real economy and not about how competitive is the banking sector given those real economic trends.

To see how this distinction matters we plot in Figure 6 the average county HHI and small bank shares from 2000 through 2017. Whereas the average county small bank deposit shares exhibit a monotonic secular decline in the 2000s thus far, average county HHI fell (i.e. the average county became more competitive) leading up to the 2008 financial crisis before rising back to approximately where it started at the turn of the century. That is, while the average county in the United States experienced no overall change in market concentration, the set of banks competing in the average county shifted from smaller to larger institutions.

In Columns 3 of Table XI, we report results of an OLS regression of changes in county deposit HHI on our variable of interest, small-firm employment growth, and find no relationship between real-side small-firm dynamics and local bank competition. Similar, in Column 4, we report results of an OLS regression of changes in county deposit HHI on large-firm employment growth and similarly find no effect. Thus, small-firm employment seems to affect who competes in a county, rather than the level of competition.

E. Mergers

Given our definition of "small" banks as those below $1 billion, the county-level small bank measurements can be affected by small firm employment growth through at least four distinct mechanisms. Small banks could be acquired by larger banks, ceasing to be designated as "small." Small banks could themselves acquire other small banks to grow out of the small bank classification. Small banks can fail. Finally, small banks can organically grow out of the definition. Theories and existing literature on relationship banking suggests that the first mechanism, acquisition by another bank, is the most likely mechanism through which small firm employment affects small banks. In particular, our paper relies on the view that small banks have a comparative advantage in small business lending. If small business lending struggles, then a small bank would not be expected to capitalize on this advantage through organic growth or acquisition. For example, Berger, Saunders, Scalise, and Udell (1998) find that acquired institutions adopt the lending strategies of their acquirer. Thus, a small bank facing a decline in small firm customers would be unlikely to capitalize on their comparative advantage through acquiring another institution. While it seems theoretically possible for small firm employment to affect small bank deposit and branches through failure, we expect that failures are more likely the consequence of larger regional and macroeconomic trends.

To examine the mechanisms through which small-bank deposit growth may occur, we measure small bank deposits (branches) affected by acquisition,[25] acquiring another institution, and failing. We relate these measures to small-firm employment growth. However, mergers and failures happen at a bank level and not a geographic level. To measure small-bank mergers and failures at the county level, we use the ratio of small-bank deposits associated with acquisition to total deposits (and similarly in the case of acquiring and failed small-banks), reported in Table I. Approximately 1.5 percent of deposits in an average county-year are associated with an acquired small bank, 1.9 percent of deposits in an average county-year are associated with an acquiring small bank, and approximately 0.2 percent of deposits in an average county-year are associated with a failed small bank.

In Table XII, we relate measures of acquired, acquiring, and failed small banks to our variable of interest, small-firm employment growth. To remain consistent with the baseline specification, we report results using OLS and two-stage least square frameworks.[26] In Columns 1 through 3, we report results of regressions of acquired small-bank deposits to total county deposits. Columns 1 and 2 show a strong statistical relationship between log differences in small-firm employment and acquired small-bank deposits, using county controls and county fixed effects, respectively. Increased small-firm employment is associated with lesser acquired small-bank deposits. In Column 3, we show that the relationship holds using the two-stage least squares specification. In Columns 4 through 6, we define $AcqHQ$ equal to one if there is small bank headquartered in the county acquired during the year and zero

[25] We exclude intracompany merger in our merger definition, where an "intracompany" acquisition is defined as a merger in which the institutions belonged to the same holding company for less than one year prior to the merger.

[26] In unreported analysis, we find results of similar statistical significance using similar tobit specifications as to what is reported in the table. However, because we cannot use county fixed effects in a Tobit specification, we opt to report results using linear regression models.

otherwise. Columns 4 and 5 show a strong statistical relationship between log differences in small-firm employment and acquired small bank, using county controls and county fixed effects, respectively. Increased small-firm employment is associated with a lower propensity for a bank headquartered in the county to be acquired. In Column 6, we show that the relationship holds using the two-stage least squares specification.

In Columns 7 through 8, we report results of regressions of small-bank deposits associated with an acquiring small bank to total county deposits. Both with county controls and county fixed effects, we do not find a statistically significant relationship. In Columns 9 through 10, we report results of regressions of small-bank deposits associated with a failed small bank to total county deposits. Given the dearth of failures during the sample period prior to the financial crisis, we restrict attention to 2008 to 2017. Again, both with county controls and county fixed effects, we do not find a statistically significant relationship. Thus, we find that on the external margin, our results are driven by the higher propensity of small banks to be acquired when small-firm employment declines or, alternatively, the lower propensity of small banks to be acquired when small-firm employment increases.

V. Employment and Small Business Lending

In our analysis, we rely upon QWI data on employment by firm size to measure changes in the aggregate size and performance of small businesses. Meanwhile, our narrative focuses on changes in the demand for financial services from small businesses. While this may include a variety of services, the extant literature points to small-business loans as an integral part of small-business finance. In this section, we examine how our measure of small-business financial services demand from the QWI data corresponds to measures of small-business borrowing.

To assess the relationship between small firm employment and small business borrower, we rely upon data from the Community Reinvestment Act (CRA). CRA is intended to encourage depository institutions to help meet the credit needs of the communities in which they operate, including low- and moderate-income neighborhoods. All banks that meet an asset size threshold are subject to data collection and reporting requirements. As of December 31, 2017, the asset size threshold that triggers data collection and reporting for all agencies was $1.226 billion, and generally increases year-on-year at about the rate of inflation. We use CRA data of bank loans to businesses below certain size thresholds aggregated to the county level on an annual basis. Consequently, a limitation of the data is that it does not measure loans to small businesses per se, but rather small loans to businesses, independent of firm size. Nevertheless, CRA data has commonly been used in the literature to proxy for small-business lending (e.g., Cortés et al. (2020) and references therein).

For the purposes of our study, the asset size threshold is problematic to measure small-business lending by small banks because it explicitly excludes those banks in which we are interested. However, under the assumption that the county-level demand for small-business loans is correlated across large and small institutions, we use the CRA data to inform to what extent the demand for small business loans from small banks is correlated to our primary variable of interest, growth in small-firm employment.

In Table XIII we report results of regressions of county-level small-business lending from CRA on our measure of county-level small-firm employment from QWI. In Column 1, we report results of county-aggregate CRA loan volume growth regressed on small-firm employment growth from QWI and year 2000 county controls. We find that CRA lending growth is strongly correlated with small-firm employment. In Column 2, we find a similarly strong relationship using county fixed effects in place of year 2000 county controls. In Column 3, we add large-firm employment growth as a control and find that it is an order of magnitude smaller in explaining CRA county lending growth than small-firm employment growth and is marginally significant. In Columns 4 through 8, we use bank-county-year data to examine the relationship between small-firm employment growth and small-business lending. In Column 4, we show that our specification from Column 1 yields similar results in the bank-county-year data.

One challenge with the CRA data is that reporting specifically excludes smaller banks. As a result, CRA county aggregates are in part a consequence of which banks report within a county. In Columns 5 through 8, we exploit the structure of the CRA data to assess the relationship of small-business lending and county small-firm employment within bank. In Column 5, we show that the relationship between QWI small-firm employment growth and CRA lending growth are strongly related after controlling for bank fixed effects. In Column 6, we should that the relationship holds across counties within a bank-year. In Column 7, we show that the relationship holds within a bank-year after controlling for county fixed effects. Finally, in Column 8, we show that the effect persists after controlling for changes in log large-firm employment. Although large-firm employment is statistically related to small-business loans measured using CRA data, the relationship between small firm employment and small business lending is an order of magnitude larger and also statistically much stronger. Together, the results of this section suggests that small-firm employment as measured in QWI is strongly related to small-business loan demand.

VI. Bartik Diagnostics

Goldsmith-Pinkham, Sorkin, and Swift (2019) (GSS) show how to construct Rotemberg weights which allow us to better understand which industries are primarily driving the estimates, and to make more concrete the set of specification tests that support the research design. In this section, we discuss the Rotemberg weights associated with our instruments.

In particular, GSS show that the Bartik instrument is effectively a weighted sum of just-identified instrumental variable estimators where each industry's share can be considered as its own instrument. They then show that the Bartik estimator ($\hat{\beta}_{Bartik}$) can be rewritten as a weighted sum of the just-identified estimators. Mathematically:

$$\hat{\beta}_{Bartik} = \sum_t \sum_k \hat{\alpha}_{kt} \hat{\beta}_k$$

$$where$$

$$\hat{\beta}_k = (Z_k' X^{\perp})^{-1} Z_k' Y^{\perp} \ and \ \hat{\alpha}_{kt} = \frac{g_{kt} Z_k' X^{\perp}}{\sum_t \sum_{k'} g_{k't} Z_k' X^{\perp}}$$

$$so \ that \ \sum_t \sum_k \hat{\alpha}_{kt} = 1$$

where Z_k are year 2000 county shares of industry k, g_{kt} is the national small firm growth rate of industry k in year t demeaned by the industry average,[27] X is a matrix of county small-firm employment growth rates, Y is a matrix of small bank deposit growth rates, and $X^{\perp} = M_D X$ where M_D is the annihilator matrix for controls D, $M_D = I - D(D'D)^{-1}D'$ and I is the identity matrix. Denote $\hat{\alpha}_k = \sum_t \hat{\alpha}_{kt}$.

We interpret the Bartik instrument in this paper as reflecting variation in 2000 county-industry shares. Thus, we implicitly assume that those county-industry shares are exogenous to future small bank deposit growth conditional on the other covariates. The Rotemberg weights provide insight into which of the assumptions of exogeneity of county-industry shares are most important for the empirical design or, alternatively, the assumption for which our design is most sensitive to mis-specification. In Table XIV and Figures 7 and 8, we report diagnostics of Rotemberg weights as suggested by GSS.

Panel A of Table XIV shows that the bulk of the absolute weight of the estimator is absorbed by industries that receive positive weights. In Panel B, we show that the high weight industries are not necessarily higher or lower growth industries, with a correlation coefficient of -0.27. However, the high weight industries are highly correlated with first-

[27] When the industry shares sum to one within a location, the instruments are linearly dependent. To address this issue, we follow GSS, and report Rotemberg weights that come from demeaning the (unweighted) industry growth rates.

stage F-statistics, which is also borne out in Figure 7. This is an important diagnostic, as it reveals that the high-weight industries act as strong instruments. In addition, the high-weight industries are also associated with industries with more industry share variation across counties (correlation coefficient 0.450). In Panel C, we show that much of the absolute weight of the instrument is absorbed by two years in the data, 2009 and 2016. Panel D of Table XIV indicates that, consistent with Figure 7 the top five industries absorb nearly the entirety of the absolute weight of the estimator and the top two industries (Mining, Quarrying, and Gas Extraction; and Manufacturing) receive more than 70 percent of the absolute weight of the estimator. Thus, our identifying assumption can be best understood as an assumption that conditional on other covariates, county employment shares for these two industries in 2000 is not driven by future innovations to small-bank deposit growth, especially for 2009 and 2016. Panel D shows that the point estimates across the top-five industries. The just-identified parameter estimates for the top-five industries range from 0.431 (Mining, Quarrying, and Gas Extraction) to 2.082 (Manufacturing), though the confidence interval generally overlap (with manufacturing the one exception). Thus, it appears that individual industry shares that drive our findings provide similar, if noisy, estimates.

In Figure 8 we plot the first-stage F-statistics against the just-identified estimators β_k to understand the heterogeneity of the just-identified instruments. We restrict attention to only those instruments with a first-stage F-statistic greater than 5, consistent with GSS. The circles in the graph represent industries with positive Rotemberg weights, while the diamonds reflect industries with negative Rotemberg weights and the size of the shapes reflect the magnitude of the weight $\hat{\alpha}_k$. Similar to Panel D in Table XIV, the plot demonstrates that the strongest first-stage industries in our analysis produce estimates similar to our Bartik estimator (i.e. centered around 0.9). However, we note that some of the low Rotemberg weight industries with F-statistics produce more varied β estimates.

In Figure 9 we highlight the counties that are in the top five percent of year 2000 county industry shares for those industries that received the highest Rotemberg weights according to XIV. We note strong concentrations in Nevada, western North Dakota, and western Texas, driven by Mining, Quarrying, and Gas Extraction. However, counties with high industry shares for the other counties driving our parameter estimates appear to be distributed across the United States.

Analysis of the Rotemberg weights from the baseline analysis suggests that Mining, Quarrying, and Gas Extraction, Construction, and Manufacturing provide most of the variation upon which the instrument relies.[28] To better understand how our instrument relies upon these industries, we run a similar analysis using 3-digit NAICS codes. In general, we find similar results to those presented in this paper, though the first-stage F-statistics are slightly weaker. Nevertheless, the exercise allows us to better understand the industries that drive our parameter estimates. In Table XV we report the Rotemberg weights for the baseline specification (small-bank deposit growth on small-firm employment growth with county fixed effects) using three-digit NAICS codes. Similar to the case with two-digit NAICS codes, we find that the estimates are primarily driven by Mining, Quarrying, and Gas Extraction, Construction, and Manufacturing, with Support Activities for Mining (NAICS 213) accounting for the bulk of the weight and Oil and Gas Extraction (NAICS 211) accounting for the majority of the remainder. The small-firm employment share for these industries are 40.7 and 28.7 percent, respectively. Within Construction, we find that the bulk of the Rotemberg weights are driven by Specialty Trade Contractors (NAICS 238), an industry dominated by small firms, which account for 82.6 percent of industry employment. Within Manufacturing, Wood Product Manufacturing (NAICS 321), which has a small-firm employment share of 50.3 percent employment drives the weight. In each case, the just-identified parameter estimate on small-firm, on small-bank deposit shares for these four industries are statistically greater than zero, with estimates ranging from 0.38 to 1.2. Forestry and Logging (NAICS 113) is the industry with the fifth largest Rotemberg weight, though the parameter estimate has the opposite sign and it was not possible to successfully define a confidence interval.

[28]Given the large weight on Mining, Quarrying, and Gas Extraction, in unreported analysis, we run our baseline specification excluding any counties for which the industry has a non-zero industry share. We find that the parameters of interest in our baseline two-stage least squares specification and the first-stage F-statistics of that specification are robust.

VII. Conclusions

Consolidation has become ubiquitous across the economy, including in agriculture, manufacturing, and retail. The banking and finance industry is no exception to this general trend; the number of small banks has steadily decreased for the last several decades, while the largest firms control an ever increasing market share. In this paper, we argue that the dramatic consolidation of the financial industry is at least partially a consequence of consolidation on the real side of the economy. Small banks disproportionately rely on small businesses as their principle borrowers. The traditional understanding of this is that small banks rely on their relationships with these small borrowers, granting them better information than can be accessed by the larger banks. As firms in non-bank industries consolidate, be that due to technological advancement, economies of scale, or monopolistic rents, the smaller firms that form the foundation of the relationship-lending business model begin to disappear. With fewer borrowers, small banks face a lower demand for their relationship-based loan products, leading to a market that can support fewer small banks.

In this paper, we find consistent evidence that consolidation on the real side of the economy *causes* consolidation among banks. When employment at small-firms decreases by one standard deviation (approximately 7%), the deposit market share of small banks decreases by between 6 and 7%. This relationship extends to the lending side of the balance sheet, as well. Decreases in small-firm employment are correlated with decreases in growth of small loans to businesses, but less so for residential real estate growth, a sector less associated with relationship lending. The connections between small firms and small banks is particularly strong in urban areas, relative to rural areas. It is also related to the competitiveness of the market that the banks are participating in, with the effect being highest in the least competitive counties.

Taken in the context of the extant literature, which finds that the bank consolidation reduces small-business lending, our results suggest a feedback loop between the real and financial sectors. Our findings complement existing views that regulation and technology have contributed to bank and real-side consolidation. The results highlight that the viability of small banks may depend on the viability of small firms. From a policy perspective, many existing policies seek to support small businesses by supporting small banks. Our results suggest that the converse may be true, as well: If policy makers wish to support small, community banks, supporting small business will be an effective but previously unrecognized channel.

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Table I: Source: Census, QWI, and SOD data. Difference variables expressed as annual differences (e.g. the difference between 2003 and 2002).

	Annual County Data, 2003-2017			
	mean	p50	sd	count
Census QWI				
Δln(SmFirmEmp+1)	0.0008	0.0042	0.0723	36526
Δln(LgFirmEmp+1)	0.0106	0.0103	0.2026	36526
ΔSm Firm Emp Share	-0.0019	-0.0014	0.0394	36526
ΔLg Firm Emp Share	0.0015	0.0010	0.0387	36526
SOD				
Δln(Sm Bank Dep+1)	0.0115	0.0295	0.2328	36526
Δln(Lg Bank Dep+1)	0.1442	0.0000	1.5100	36526
ΔSm Bank Dep Share	-0.0062	0.0000	0.0655	36526
ΔLg Bank Dep Share	0.0063	0.0000	0.0597	36526
Δln(Sm Bank Brch+1)	-0.0160	0.0000	0.1320	36526
Δln(Lg Bank Brch+1)	0.0224	0.0000	0.1934	36526
Call Report				
Sm Bank ROA	0.0120	0.0126	0.0141	34976
Sm Bank ROE	0.1139	0.1184	0.1353	34976
Sm Bank Prov/Asset	0.0044	0.0023	0.0071	34976
Δln(Sm Bank Sm Loans+1)	-0.0109	0.0060	0.2443	34976
Δln(Sm Bank CI +1)	0.0059	0.0248	0.2679	34976
Δln(Sm Bank Res RE+1)	0.0111	0.0221	0.2145	34976
Mergers				
Sm Bank Dep Acquired/Total Deposits	0.0151	0.0000	0.0664	36526
Sm Bank Acquirer Dep/Total Deposits	0.0185	0.0000	0.0768	36526
Failed Sm Bank Dep/Total Deposits	0.0018	0.0000	0.0254	36526

Table II: Source: Census, QWI, and SOD data. Cumulative 5 year changes.

	2002-2007				2007-2012				2012-2017			
	mean	p50	sd	count	mean	p50	sd	count	mean	p50	sd	count
ΔLn(Small Firm Emp+1)	0.0485	0.0371	0.1327	2447	-0.0569	-0.0610	0.1382	2450	0.0200	0.0250	0.1351	2453
ΔLn(Large Firm Emp+1)	0.0656	0.0563	0.4153	2447	0.0028	-0.0068	0.3779	2450	0.0921	0.0904	0.3181	2453
ΔLn(Small Bank Dep+1)	0.0981	0.1659	1.5531	2447	-0.1330	0.1313	1.6939	2450	-0.2307	0.0387	2.0449	2453
ΔLn(Large Bank Dep+1)	1.7676	0.1621	3.8204	2447	0.4445	0.0000	2.2480	2450	-0.0503	0.0000	2.2947	2453
ΔLn(Small Bank Brnch+1)	-0.0202	0.0000	0.3335	2447	-0.1051	0.0000	0.3165	2450	-0.1540	0.0000	0.3379	2453
ΔLn(Large Bank Brnch+1)	0.2968	0.0000	0.4864	2447	0.1054	0.0000	0.3403	2450	-0.0679	0.0000	0.2624	2453
ΔSmall Bank Dep Share	-0.0303	0.0000	0.1601	2447	-0.0352	0.0000	0.1504	2450	-0.0443	-0.0017	0.1479	2453
ΔSmall Firm Emp Share	-0.0032	-0.0050	0.0717	2447	-0.0104	-0.0114	0.0643	2450	-0.0153	-0.0106	0.0623	2453
ΔLarge Bank Dep Share	0.0645	0.0000	0.1414	2447	0.0276	0.0000	0.1085	2450	0.0029	0.0000	0.0849	2453
ΔLarge Firm Emp Share	-0.0001	0.0028	0.0720	2447	0.0106	0.0113	0.0653	2450	0.0126	0.0096	0.0623	2453

Table III: Multivariate regressions of small bank deposit growth. Errors clustered at the state level.

VARIABLES	(1) $\Delta\ln(\text{SmDep})$	(2) $\Delta\ln(\text{SmDep})$	(3) $\Delta\ln(\text{SmDep})$	(4) $\Delta\ln(\text{SmDep})$	(5) $\Delta\ln(\text{SmDep})$	(6) $\Delta\ln(\text{SmDep})$	(7) $\Delta\ln(\text{SmDep})$	(8) $\Delta\ln(\text{SmDep})$
$\Delta\ln(\text{SmFirmEmp})$	0.0915***	0.0929***	0.0888***				0.0899***	0.0789***
	(0.0167)	(0.0168)	(0.0189)				(0.0187)	(0.0185)
$\Delta\ln(\text{LgFirmEmp})$				0.00392	0.00295	0.00300	0.00517	0.00284
				(0.00549)	(0.00578)	(0.00523)	(0.00493)	(0.00511)
$\ln(\text{pop}_{2000})$		-0.0126***			-0.0121***			
		(0.00292)			(0.00302)			
unemp_{2000}		0.000124			3.48e-05			
		(0.00138)			(0.00137)			
$\text{urban}_2 000$		-0.00408			-0.00364			
		(0.00675)			(0.00673)			
$\ln(\text{inc}_{2000})$		-0.0120			-0.0114			
		(0.0123)			(0.0123)			
$\ln(\text{branch}_{2000})$		0.00298			0.00233			
		(0.00309)			(0.00319)			
SmDepShare_{2000}		-0.0303***			-0.0305***			
		(0.00604)			(0.00609)			
$\Delta\ln(\text{pop})$								-0.200***
								(0.0646)
$\Delta\ln(\text{inc})$								0.0876***
								(0.0219)
Observations	36,526	36,069	36,526	36,526	36,069	36,526	36,526	36,069
R-squared	0.007	0.011	0.060	0.007	0.010	0.059	0.060	0.063
REG	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
YEAR	NO	YES	YES	YES	YES	YES	YES	YES
COUNTY FE	NO	NO	YES	NO	NO	YES	YES	YES
YRS	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table IV: Multivariate regressions of small firm employment growth. The Bartik instrument is constructed as the weighted sum of national industry small employment growth, where the weights are year 2000 county industry shares. Column (1) reports regression results of small firm employment growth on year 2000 controls. Columns (2) though (6) report regression results of small firm employment growth on the Bartik instrument constructed using industry share exposures to national industry trends on small-firm employment growth. Columns (7) and (8) report regression results of large-firm employment growth on the Bartik instrument constructed using industry share exposures to national industry trends on large-firm employment growth. Errors clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Δln(SmEmp)	Δln(SmEmp)	Δln(SmEmp)	Δln(SmEmp)	Δln(SmEmp)	Δln(SmEmp)	Δln(LgEmp)	Δln(LgEmp)
Bartik_{small}		1.004***	1.172***	0.820*	0.930***	1.108**		
		(0.133)	(0.150)	(0.421)	(0.172)	(0.420)		
Bartik_{large}							1.579***	1.646***
							(0.143)	(0.207)
$\ln(\text{pop}_{2000})$	0.00589***	0.00625***					0.00296	
	(0.00184)	(0.00160)					(0.00335)	
$\text{unemp}_{2000})$	-0.000977**	-0.00141***					-0.00143*	
	(0.000383)	(0.000388)					(0.000738)	
urban_{2000}	0.00495***	0.00462***					0.00624***	
	(0.00128)	(0.00133)					(0.00185)	
$\ln(\text{income})_{2000}$	0.00661***	0.00360					0.00153	
	(0.00207)	(0.00215)					(0.00505)	
$\ln(\text{branches})_{2000}$	-0.00720***	-0.00723***					-0.00518	
	(0.00188)	(0.00157)					(0.00320)	
SmDepShare_{2000}	-0.00218	-0.00129					-0.000140	
	(0.00282)	(0.00258)					(0.00560)	
Observations	36,069	36,069	36,526	12,250	12,276	12,301	36,069	36,526
F-statistic		57.0	61.0	3.8	29.2	7.0	121.9	63.2
R-squared	0.075	0.085	0.122	0.157	0.278	0.176	0.017	0.052
REG	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
YEAR	YES	YES	YES	YES	YES	YES	YES	YES
COUNTY FE	NO	NO	YES	YES	YES	YES	NO	YES
YRS	2003-2017	2003-2017	2003-2017	2003-2007	2008-2012	2013-2017	2003-2017	2003-2017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table V: Regressions of log differences in small bank deposits variables on log differences in small firm employment. Column (1) and (2) report results from an OLS regression of log differences in small bank deposits on the Bartik instrument using exposure to national trends in industry small-firm employment growth. Column (3)-(6) report results from an 2SLS regression of log differences in small-bank deposits on log differences in small-firm employment using a Bartik instrument constructed with exposure to national trends in industry small-firm employment growth. Column (7) and (8) report results from an 2SLS regression of log differences in small-bank deposits on log differences in large-firm employment using a Bartik instrument constructed with exposure to national trends in industry large-firm employment growth. Column (9) and (10) report results from an 2SLS regression of log differences in small-bank deposits on both log differences in small-firm employment and log differences in large-firm employment using two Bartik instruments, one constructed with exposure to national trends in industry small-firm employment growth and one constructed with exposure to national trends in industry large-firm employment growth. Errors clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Δln(SmDp)	Δln(SmDp)	Δln(SmDp)	Δln(SmDp)	Δln(SmDep)	Δln(SmDp)	Δln(SmDp)	Δln(SmDp)	Δln(SmDp)	Δln(SmDp)
Bartik$_{small}$	0.868***	1.061***								
	(0.193)	(0.207)								
$\Delta \widehat{ln(SmEmp)}$			0.869***	1.505**	0.906***	0.812***			1.137***	0.997***
			(0.164)	(0.690)	(0.178)	(0.183)			(0.401)	(0.363)
$\Delta \widehat{ln(LgEmp)}$							0.365***	0.447***	-0.220	-0.177
							(0.101)	(0.0901)	(0.272)	(0.253)
ln(pop$_{2000}$)	-0.0117***		-0.0172***	-0.0219*			-0.0128***			
	(0.00282)		(0.00303)	(0.0123)			(0.00274)			
umemp$_{2000}$	-0.000344		0.000882	0.00223			0.000183			
	(0.00133)		(0.00143)	(0.00234)			(0.00132)			
urban$_{2000}$	-0.00388		-0.00792	-0.0136**			-0.00664			
	(0.00679)		(0.00619)	(0.00630)			(0.00637)			
ln(inc$_{2000}$)	-0.0139		-0.0171	-0.00943			-0.0151			
	(0.0123)		(0.0121)	(0.0125)			(0.0123)			
ln(branch$_{2000}$)	0.00216		0.00856***	0.0193			0.00434			
	(0.00296)		(0.00326)	(0.0149)			(0.00285)			
SmDpShare$_{2000}$	-0.0297***		-0.0286***	-0.0324*			-0.0298***			
	(0.00594)		(0.00616)	(0.0190)			(0.00604)			
Δln(pop)						-0.182***				-0.187***
						(0.0598)				(0.0587)
Δln(inc)						0.00512				0.00358
						(0.0401)				(0.0419)
Observations	36,117	36,574	36,069	36,069	36,526	36,069	36,069	36,526	36,526	36,069
REG	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTY FE	NO	YES	NO	NO	YES	YES	NO	YES	YES	YES
YRS	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table VI: Growth at 5-year intervals. In Column 1 we report regression results of log differences in small firm employment on the Bartik instrument constructed with national small-firm employment growth by industry with four lags. In Column 2 we report regression results of log differences in small firm employment on autoregressive log differences. In Columns 3 through 6 we report the results of OLS regressions of log changes in small-bank deposits on log changes in small-firm employment with different covariates using three 5-year intervals (2002-2007, 2007-2012, 2012-2017). Column 7 reports the first stage regression of the 5-year small-firm employment growth on the Bartik instrument constructed with national 5-year small firm industry trends using the same three 5-year intervals. Column 8 reports results of a two stage regression of 5-year small-bank deposit on 5-year small firm employment growth using the same three 5-year intervals. Errors clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$\Delta\ln(SmEmp)_{1yr}$	$\Delta\ln(SmEmp)_{1yr}$	$Bartik_{1yr}$	$\Delta\ln(SmDp)_{5yr}$	$\Delta\ln(SmDp)_{5yr}$	$\Delta\ln(SmDp)_{5yr}$	$\Delta\ln(SmEmp)_{5yr}$	$\Delta\ln(SmDp)_{5yr}$
$Bartik_{1yr}$	1.281***							
	(0.179)							
L.$Bartik_{1yr}$	0.211*		0.142***					
	(0.114)		(0.00632)					
L2.$Bartik_{1yr}$	0.120							
	(0.114)							
L3.$Bartik_{1yr}$	0.323**							
	(0.131)							
L4.$Bartik_{1yr}$	0.279**							
	(0.131)							
L.$\Delta\ln(SmEmp)_{1yr}$		-0.193***						
		(0.0196)						
$\Delta\ln(SmEmp)_{5yr}$				0.391***	0.403***	0.401***		0.546**
				(0.0616)	(0.105)	(0.104)		(0.269)
$\Delta\ln(LgEmp)_{5yr}$						0.00857		
						(0.0201)		
$Bartik_{5yr}$							1.757***	
							(0.243)	
Observations	31,550	36,485	36,526	7,066	7,155	7,155	7,155	7,155
R-squared	0.138	0.146	0.936	0.050	0.315	0.315	0.385	
REG	OLS	OLS	OLS	OLS	OLS	OLS	OLS	2SLS
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
COUNTY FE	YES	YES	YES	NO	YES	YES	YES	YES
CONTROLS FE	NO	NO	NO	YES	NO	NO	NO	NO
YRS	2006-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table VII: Regressions of log differences in small bank loans on log differences in small firm employment. Columns (1) through (3) report results from 2SLS regressions of log differences in county aggregate small-bank small CI and agricultural loans on combinations of instrumented log differences in small-firm employment using exposure to national trends in industry small-firm employment growth and on log differences in large-firm employment instrumented using exposure to national trends in industry large-firm employment growth. Columns (4) through (6) report results from 2SLS regressions of log differences in county aggregate small-bank CI loans on combinations of instrumented log differences in small-firm employment using exposure to national trends in industry small-firm employment growth and on log differences in large-firm employment instrumented using exposure to national trends in industry large-firm employment growth. Columns (7) through (9) report results from 2SLS regressions of log differences in county aggregate small bank residential real estate loans on combinations of instrumented log differences in small-firm employment using exposure to national trends in industry small-firm employment growth and on log differences in large-firm employment instrumented using exposure to national trends in industry large-firm employment growth. Errors clustered at the state level.

VARIABLES	(1) Δln(SmSBLoan)	(2) Δln(SmSBLoan)	(3) Δln(SmSBLoan)	(4) Δln(SmCI)	(5) Δln(SmCI)	(6) Δln(SmCI)	(7) Δln(SmRE)	(8) Δln(SmRE)	(9) Δln(SmRE)
$\Delta ln(\widehat{SmEmp})$	0.0677***	0.0668***	0.831***	0.121***	0.120***	0.929***	0.0359*	0.0359*	0.629***
	(0.0238)	(0.0235)	(0.202)	(0.0208)	(0.0209)	(0.203)	(0.0212)	(0.0212)	(0.168)
$\Delta ln(\widehat{LgEmp})$		-0.00520			-0.00593			-4.37e-05	
		(0.00813)			(0.00843)			(0.00544)	
Observations	34,966	34,966	34,966	34,968	34,968	34,968	34,968	34,968	34,968
REG	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTY FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
YRS	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table VIII: Regressions of county small-bank income variables on log differences in small firm employment. Columns (1) through (3) report results from 2SLS regressions of log differences in county aggregate small bank ROA on combinations of instrumented log differences in small-firm employment using exposure to national trends in industry small-firm employment growth and on log differences in large-firm employment instrumented using exposure to national trends in industry large-firm employment growth. Columns (4) through (6) report results from 2SLS regressions on log differences in county aggregate small bank ROE on combinations of instrumented log differences in small-firm employment using exposure to national trends in industry small-firm employment growth and on log differences in large-firm employment instrumented using exposure to national trends in industry large-firm employment growth. Columns (7) through (9) report results from 2SLS regressions of log differences in county aggregate small bank loan loss provisions to average bank assets on combinations of instrumented log differences in small-firm employment using exposure to national trends in industry small-firm employment growth and on log differences in large-firm employment instrumented using exposure to national trends in industry large-firm employment growth. Errors clustered at the state level.

VARIABLES	(1) ROA	(2) ROA	(3) ROA	(4) ROE	(5) ROE	(6) ROE	(7) Prov	(8) Prov	(9) Prov
$\Delta ln(\widehat{SmEmp})$	0.00637***	0.00626***	0.0243***	0.0784***	0.0794***	0.296***	-0.00509***	-0.00521***	-0.0131***
	(0.00192)	(0.00190)	(0.00785)	(0.0242)	(0.0243)	(0.0909)	(0.00116)	(0.00117)	(0.00482)
$\Delta ln(\widehat{LgEmp})$		0.000498*			0.00548*			-0.000610***	
		(0.000256)			(0.00277)			(0.000216)	
Observations	35,216	34,799	35,216	35,216	35,216	35,216	35,216	35,216	35,216
REG	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTY FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
YRS	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table IX: Regressions of log differences in small bank deposits variables on log differences in small firm employment across subsample periods. Columns (1) and (2) report results from baseline regressions in for the years 2003 to 2007, inclusive. Columns (3) and (4) report results from baseline regressions in for the years 2008 to 2012, inclusive. Columns (5) and (6) report results from baseline regressions in for the years 2013 to 2017, inclusive. Odd numbered columns report results from OLS regressions of the outcome variable on the Bartik instrument using exposure to national small-firm employment trends by industry. Even numbered columns report results from 2SLS regressions of the outcome variable on log differences in small firm employment using the small-firm employment Bartik instrument. Errors clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Δln(SmDep)	Δln(SmDep)	Δln(SmDep)	Δln(SmDep)	Δln(SmDep)	Δln(SmDep)
Bartik_{small}	2.175**		0.968**		0.974**	
	(0.833)		(0.417)		(0.381)	
$\Delta ln(\widehat{SmEmp})$		2.732*		1.041**		0.853***
		(1.488)		(0.421)		(0.257)
Observations	12,190	12,167	12,205	12,190	12,179	12,169
REG	OLS	2SLS	OLS	2SLS	OLS	2SLS
YEAR FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
YRS	2003-2007	2003-2007	2008-2012	2008-2012	2013-2017	2013-2007
Number of geography		2,460		2,462		2,462

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table X: Regressions of log differences in small bank deposits variables on log differences in small firm employment across different geographies. Columns (1) through (3) report results from baseline regressions for declining levels of urbanization based on the year 2000 classification (urban, micropolitan, rural). Columns (4) through (6) report results from baseline regressions for declining levels of county deposit concentration (measured by HHI). Errors clustered at the state level.

	Urbanization Level			HHI Terciles		
	(1)	(2)	(3)	(4)	(5)	(6)
	Urban	Micro	Rural	High Conc	Mid Conc	Low Conc
VARIABLES	Δln(SmDep)	Δln(SmDep)	Δln(SmDep)	Δln(SmDep)	Δln(SmDep)	Δln(SmDep)
$\Delta ln(\widehat{SmEmp})$	1.982**	1.434***	0.614**	1.566***	0.817***	0.868***
	(0.915)	(0.488)	(0.241)	(0.424)	(0.252)	(0.164)
Observations	5,493	16,327	14,706	12,307	12,259	11,960
REG	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
YEAR FE	YES	YES	YES	YES	YES	YES
COUNTY FE	YES	YES	YES	YES	YES	YES
YRS	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XI: Alternative Specifications. Columns (1) reports results from an OLS regression of large-bank deposit growth on small-firm employment growth. Column (2) reports results from a two-stage least square regression of large-bank deposit growth on small-firm employment growth, using the Bartik instrument constructed with national small-firm employment trends by industry. Columns (3) and (4) report results from OLS regressions of changes in county deposit HHI on small-firm employment growth and large-firm employment growth, respectively. Errors clustered at the state level.

	(1)	(2)	(3)	(4)
VARIABLES	Δln(LgDep)	Δln(LgDep)	ΔHHI	ΔHHI
Δln(SmEmp)	0.0145	0.121	-0.00322	
	(0.0115)	(0.121)	(0.00317)	
Δln(LgEmp)				6.95e-05
				(0.000871)
Observations	36,043	36,043	36,526	36,526
R-squared	0.106		0.057	0.057
REG	2SLS	2SLS	2SLS	2SLS
YEAR FE	YES	YES	YES	YES
COUNTY FE	YES	YES	YES	YES
YRS	2003-2017	2003-2017	2003-2017	2003-2017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XII: Regressions of changes in small-bank structure and small-firm employment growth. Columns 1 through 3 report regressions of the proportion of small-bank deposits associated with an acquired small-bank to total county deposits on log differences in small-firm employment. Columns 1 and 2 are OLS regressions. Column 3 reports results of a 2SLS regressions where log differences in small-firm employment are instrumented with a Bartik measure using county exposure to national small-firm employment growth by industry. Columns 4 through 6 report regressions of a binary variable equal to one if a small-bank headquartered in the county is acquired and zero otherwise on log differences in small-firm employment. Columns 4 and 5 are OLS regressions. Column 6 reports results of a 2SLS regressions where log differences in small-firm employment are instrumented with a Bartik measure using county exposure to national small-firm employment growth by industry. Columns 7 through 8 report OLS regressions of the proportion of small-bank deposits associated with an acquiring small bank to total county deposits on log differences in small-firm employment. Columns 9 through 10 report OLS regressions of the proportion of small-bank deposits associated with an failed small bank to total county deposits on log differences in small-firm employment. Errors are clustered at the state level.

VARIABLES	(1) AcqDep	(2) AcqDep	(3) AcqDep	(4) AcqdHQ	(5) AcqdHQ	(6) AcqdHQ	(7) BuyerDep	(8) BuyerDep	(9) FailDep	(10) FailDep
Δ ln(SmEmp)	-0.0287***	-0.0298***	-0.231***	-0.0574***	-0.0643***	-0.356*	0.0126	0.0125	-0.00572	-0.00642
	(0.00867)	(0.00950)	(0.0717)	(0.0210)	(0.0200)	(0.197)	(0.00881)	(0.00892)	(0.00446)	(0.00548)
ln(pop_{2000})	0.000888			0.0125*			-0.00374**		0.000615	
	(0.00133)			(0.00690)			(0.00180)		(0.000780)	
$unemp_{2000}$	-0.000471			0.00146			-0.000844**		8.29e-05	
	(0.000435)			(0.00187)			(0.000399)		(0.000135)	
$urban_{2000}$	0.00189			0.0439***			-0.000911		0.00175	
	(0.00134)			(0.00912)			(0.00249)		(0.00142)	
ln(inc_{2000})	0.00294			0.0692***			-0.00305		-0.000240	
	(0.00297)			(0.0187)			(0.00311)		(0.000863)	
ln($branch_{2000}$)	-0.000847			0.0539***			0.00402**		-0.000674	
	(0.00141)			(0.00839)			(0.00185)		(0.000903)	
$SmDepShare_{2000}$	0.0159***			0.0607***			0.0219***		0.00133	
	(0.00188)			(0.0119)			(0.00197)		(0.000997)	
Observations	36,069	36,526	36,526	36,069	36,069	36,069	36,069	36,526	36,069	36,526
R-squared	0.008	0.077		0.100	0.210		0.013	0.113	0.013	0.089
REG	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	OLS	OLS
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
YRS	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017	2003-2017

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XIII: OLS regressions of County Small Business Lending on County Small Firm Employment. In each specification, the independent variable is the log change in small business lending. County small business lending is measured using Community Reinvestment Act data and is aggregated to the county-year level for Columns 1-3 and the bank-county-year for Columns 4-8. Errors clustered at the state level.

	(1) ΔLn(SBLn)	(2) ΔLn(SBLn)	(3) ΔLn(SBLn)	(4) ΔLn(SBLn)	(5) ΔLn(SBLn)	(6) ΔLn(SBLn)	(7) ΔLn(SBLn)	(8) ΔLn(SBLn)
ΔLn(Small Firm Emp)	0.137***	0.111**	0.116**	0.124***	0.123***	0.135***	0.112***	0.115***
	(0.0453)	(0.0458)	(0.0456)	(0.0253)	(0.0247)	(0.0240)	(0.0239)	(0.0236)
ΔLn(Large Firm Emp)			0.0215*					0.0193**
			(0.0123)					(0.00720)
Ln(Pop_{2000})	0.00351			0.0159***	0.0178***	0.0172***		
	(0.00336)			(0.00306)	(0.00216)	(0.00211)		
$Unemployment_{2000}$	0.00133			-0.00247**	-0.00286***	-0.00300***		
	(0.00112)			(0.00100)	(0.000748)	(0.000696)		
$Urban_{2000}$	0.0161***			0.00668**	0.0116***	0.0114***		
	(0.00286)			(0.00314)	(0.00306)	(0.00296)		
Ln(Per Capita Inc_{2000})	0.0145			-0.00346	0.00744	0.00498		
	(0.00874)			(0.00644)	(0.00598)	(0.00591)		
Ln($Branch_{2000}$)	-0.00638			-0.00540*	-0.00388	-0.00462*		
	(0.00401)			(0.00268)	(0.00232)	(0.00236)		
Small Bank $Share_{2000}$	0.0134*			-0.00667	-0.00392	-0.00559		
	(0.00758)			(0.00475)	(0.00375)	(0.00387)		
Observations	39,912	39,912	39,912	860,141	860,141	860,141	859,578	859,578
R-squared	0.149	0.161	0.162	0.029	0.052	0.171	0.171	0.171
REG	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
YEAR FE	YES	YES	YES	YES	YES	Abs	Abs	Abs
COUNTY FE	NO	YES	YES	NO	NO	NO	NO	YES
BANK FE	N/A	N/A	N/A	NO	YES	Abs	Abs	Abs
YRS	2002-2017	2002-2017	2002-2017	2002-2017	2002-2017	2002-2017	2002-2017	2002-2017
BANK-YEAR FE	N/A	N/A	N/A	NO	NO	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table XIV: This table reports statistics about the Rotemberg weights. When we report statistics about industry weights, we report aggregates across years. Panel A reports the share and sum of negative Rotemberg weights. Panel B reports correlations between the weights (α^k), the national component of growth (g^k), the just-identified coefficient estimates (β^k) , the first-stage F-statistic of the industry share (F^k), and the variation in the industry shares across locations ($Var(z^k)$). Panel C reports variation in the weights across years. Panel D reports the top five industries according to the Rotemberg weights. The g^k is the national industry growth rate, β^k is the coefficient from the just-identified regression, the 95% confidence interval is the weak instrument robust confidence interval using the method from Chernozhukov and Hansen (2009) over a range from -10 to 10, and Ind Share is the industry share (multiplied by 100 for legibility). Panel E reports statistics about how the values of (β^k) vary with the positive and negative Rotemberg weights.

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.056	-0.006	0.050
Positive	1.056	0.117	0.950

Panel B: Correlations of Industry Aggregates

	α_k	g_k	β_k	F_k	Var(z_k)
α_k	1				
g_k	-0.270	1			
β_k	0.186	-0.054	1		
F_k	0.718	-0.213	0.305	1	
Var(z_k)	0.290	-0.073	0.310	0.285	1

Panel C: Variation across years in α_k

	Sum	Mean
2003	-0.018	-0.001
2004	0.011	0.001
2005	0.026	0.001
2006	0.041	0.002
2007	0.033	0.002
2008	0.013	0.001
2009	0.271	0.015
2010	0.013	0.001
2011	0.080	0.004
2012	0.066	0.004
2013	0.018	0.001
2014	0.009	0.000
2015	0.061	0.003
2016	0.347	0.019
2017	0.028	0.002

Panel D: Top 5 Rotemberg weight industries

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	95 % CI	Ind Share
Mining, Quarrying, Gas Extraction	0.607	-0.113	0.431	(0.10,0.70)	1.687
Construction	0.143	-0.066	0.704	(-0.10,1.50)	6.811
Manufacturing	0.128	-0.089	2.082	(1.00,4.00)	21.550
Agriculture, Forestry, Fishing, Hunting	0.078	0.001	0.600	(-0.30,1.60)	3.652
Health Care, Social Assistance	0.059	0.089	1.291	(0.20,3.70)	12.989

Panel E: Estimates of β_k for positive and negative weights

	α-weighted Sum	Share of overall β	Mean
Negative	0.137	0.151	-1.827
Positive	0.769	0.849	0.890

Table XV: This table reports statistics about the Rotemberg weights from an analysis using 3 digit NAICS codes. When we report statistics about industry weights, we report aggregates across years. Rotemberg weights are represented by (α^k), the national component of growth (g^k), and the just-identified coefficient estimates (β^k) We report the top five industries according to the Rotemberg weights. The 95% confidence interval is the weak instrument robust confidence interval using the method from Chernozhukov and Hansen (2009) over a range from -10 to 10. A value of N/A indicates that it was not possible to define a confidence interval. Emp reflects national industry employment in 2000, $SmallShare$ represents the proportion of firms in firms with less than 250 employees in 2000 (multiplied by 100) and $IndShare$ represents the average year 2000 share of industry employment in the county.

Top 5 Rotemberg weight industries: 3 Digit NAICS

	$\hat{\alpha}_k$	g_k	β_k	95 % CI	Emp	SmallShare	Ind Share
Support Activities for Mining	0.448	-0.128	0.378	(0.20,0.60)	138,978	40.7	0.622
Oil and Gas Extraction	0.108	-0.089	0.63	(0.30,1.10)	116,794	28.7	0.374
Specialty Trade Contractors	0.062	-0.029	1.108	(0.20,2.20)	3,495,064	82.6	4.345
Wood Product Manufacturing	0.043	-0.111	1.192	(0.00,4.20)	518,505	50.3	1.924
Forestry and Logging	0.042	-0.011	-0.531	N/A	58,634	89.5	0.579

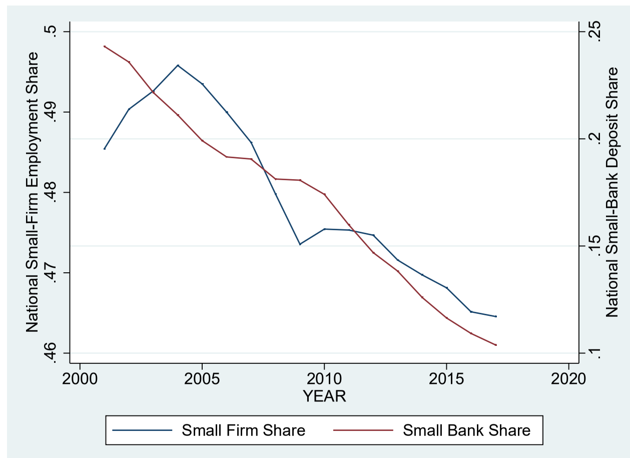

Figure 1: Source: Census Quarterly Workforce Indicators (Firm Shares). FDIC Summary of Deposits (Deposit Shares). Small Firms are defined as those with < 250 employees. Small banks are defined as those with < $1 billion in assets (constant 2010 dollars).

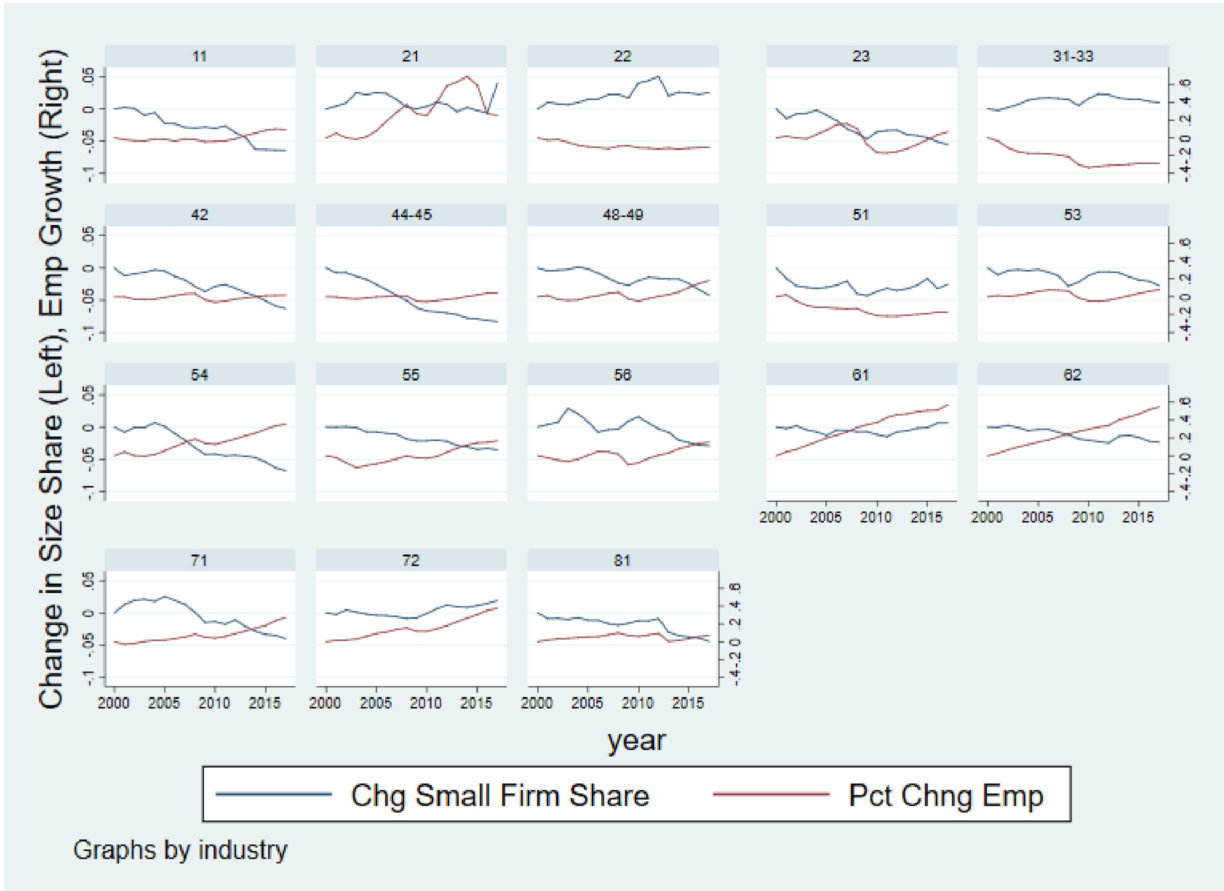

Figure 2: Source: Census Quarterly Workforce Indicators (Firm Shares). Small Firms are defined as those with < 250 employees. Sector 11: Agriculture, Forestry, Fishing and Hunting. Sector 21: Mining, Quarrying, and Oil and Gas Extraction. Sector 22: Utilities. Sector 23: Construction. Sector 31-33: Manufacturing. Sector 42: Wholesale Trade. Sector 44-45: Retail Trade. Sector 48-49: Transportation and Warehousing. Sector 51: Information. Sector 53: Real Estate and Rental and Leasing. Sector 54: Professional, Scientific, and Technical Services. Sector 55: Management of Companies and Enterprises. Sector 56: Administrative and Support and Waste Management and Remediation Services Sector 61: Educational Services. Sector 62: Health Care and Social Assistance. Sector 71: Arts, Entertainment, and Recreation. Sector 72: Accommodation and Food Services. Sector 81: Other Services (except Public Administration). Note that Sector 52: Finance and Insurance is excluded.

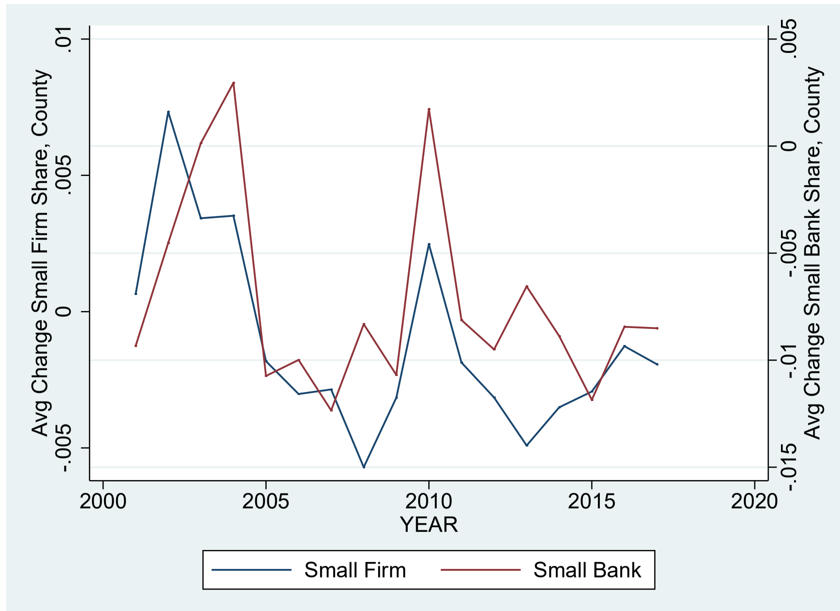

Figure 3: Source: Census Quarterly Workforce Indicators (Firm Shares). FDIC Summary of Deposits (Deposit Shares). Small Firms are defined as those with < 250 employees. Small banks are defined as those with < $1 billion in assets (constant 2010 dollars).

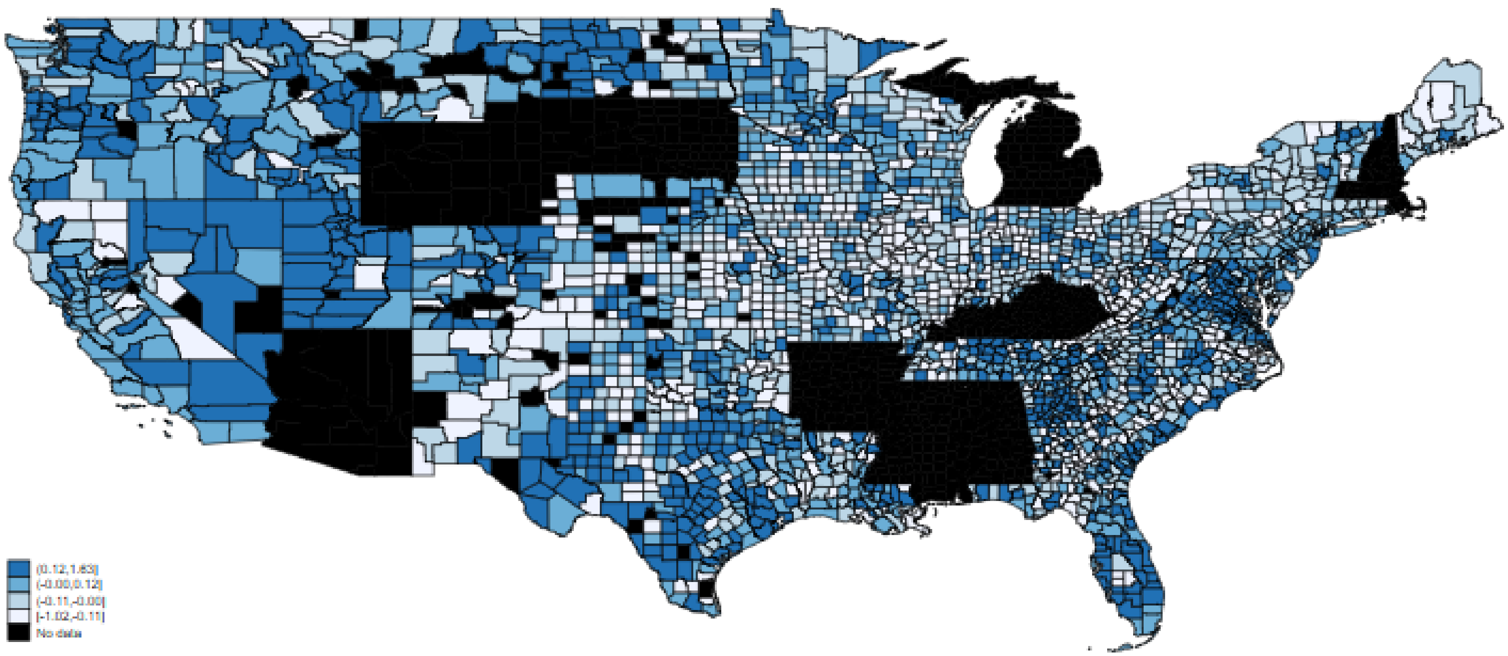

Figure 4: Source: Census Quarterly Workforce Indicators. 2002-2017 log changes in small firm employment. Small Firms are defined as those with < 250 employees.

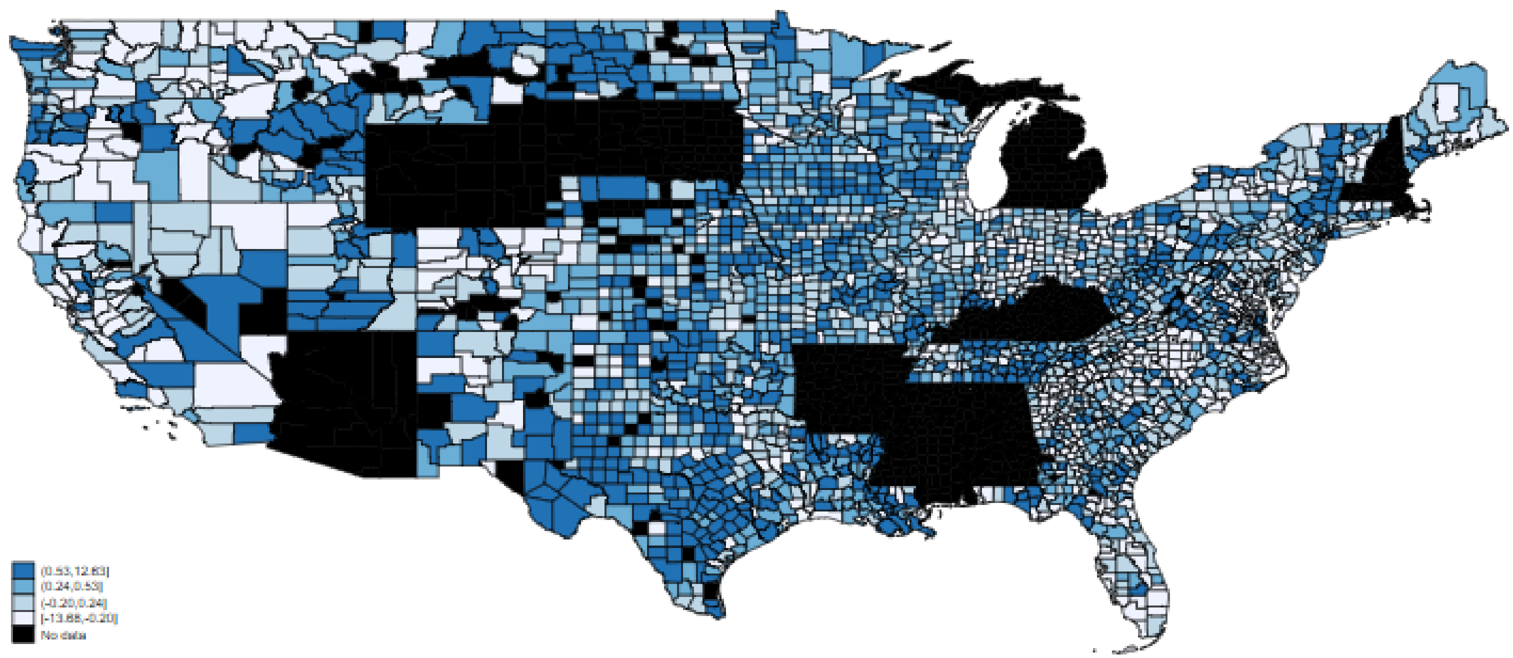

Figure 5: Source: Summary of Deposits. 2002-2017 log changes in small bank deposits. Small banks are defined as those with < $1 billion in assets.

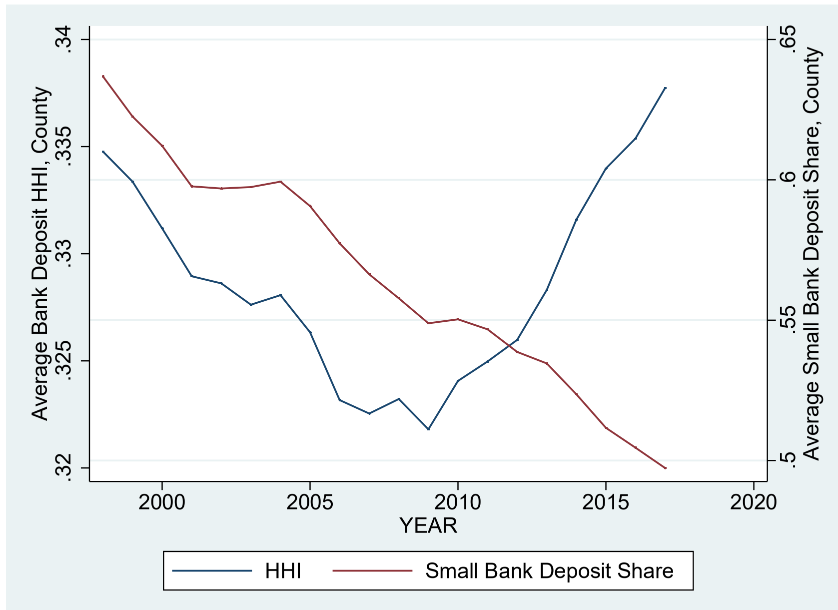

Figure 6: Source: Summary of Deposits. Small banks are defined as those with $<$ \$1 billion in assets.

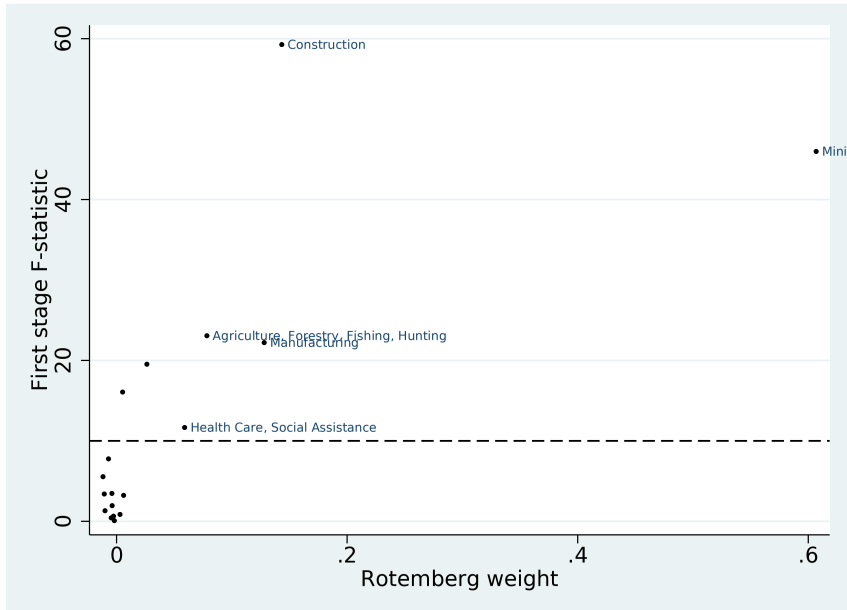

Figure 7: This figure plots the relationship between each instruments' β^k, first stage F-statistics and the Rotemberg weights. Each point is a separate instrument's estimates (industry share). The figure plots the estimated β^k for each instrument on the y-axis and the estimated first-stage F-statistic on the x-axis. The size of the points are scaled by the magnitude of the Rotemberg weights, with the circles denoting positive Rotemberg weights and the diamonds denoting negative weights. The horizontal dashed line is plotted at the value of the overall β^k. The figure excludes instruments with first-stage F-statistics below 5.

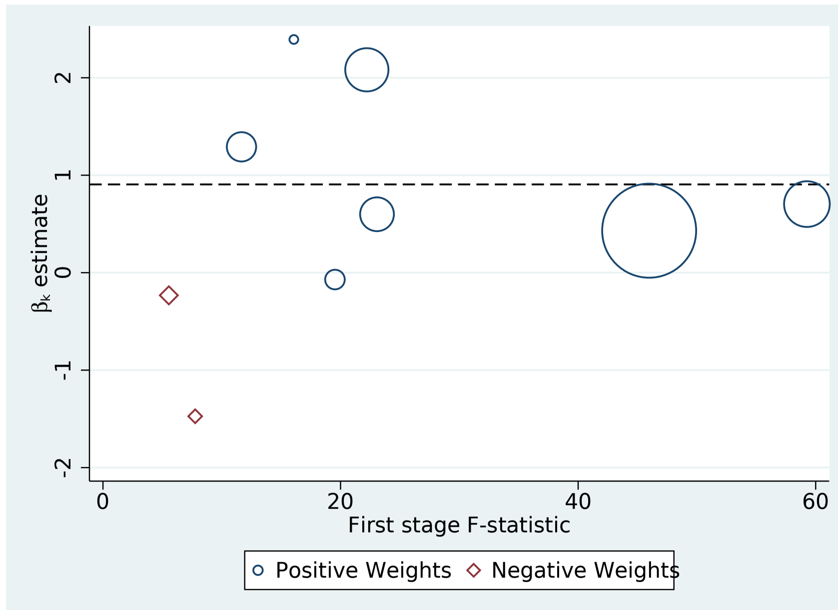

Figure 8: Heterogeneity of Just-Identified County-Share Instruments

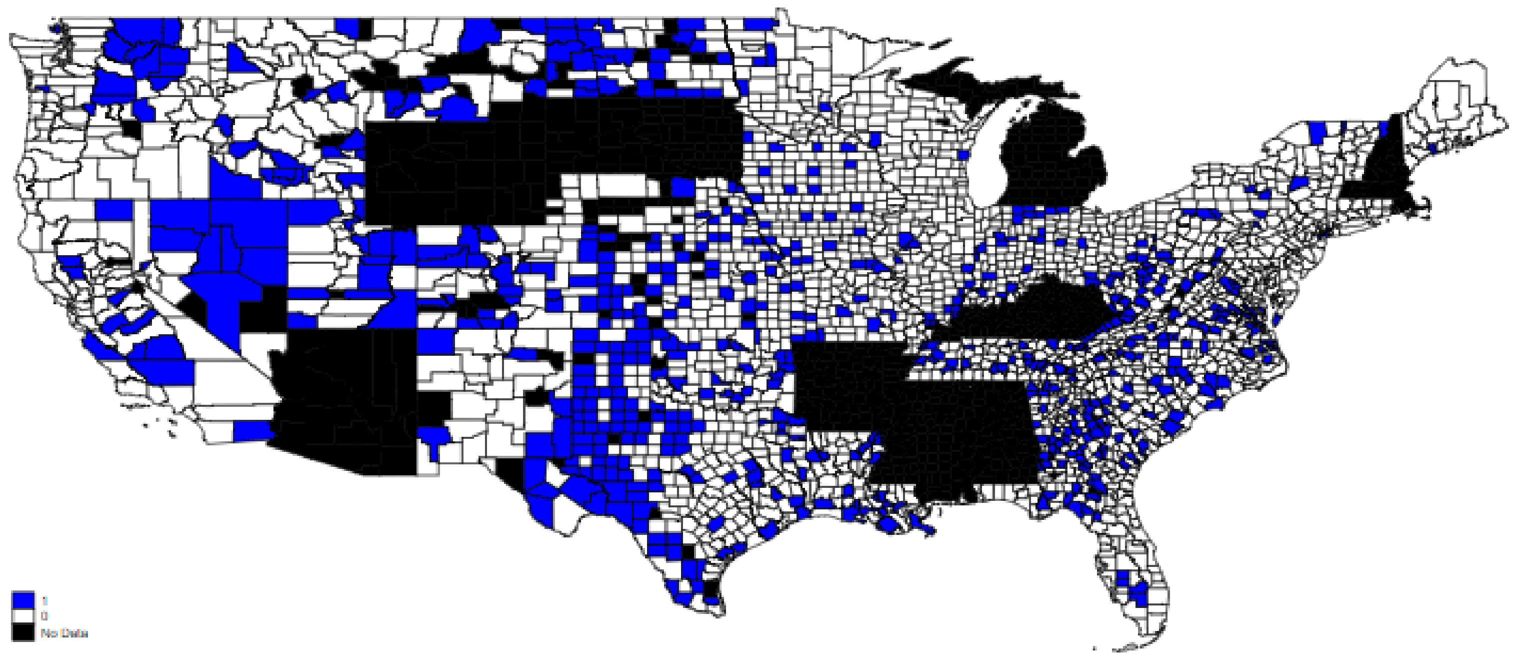

Figure 9: Source: Census QWI. Counties labeled with a “1” lie in the 95th percentile or higher of year 2000 county-industry shares for at least one industry with a Top 5 Rotemberg weight according to Table XIV and those labeled with a “0” lie below the 95th percentile of year 2000 county-industry shares for all industries with Top 5 Rotemberg weights.