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Shared Destinies? Small Banks and Small Business Consolidation*

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Abstract

We identify a new source of consolidation in the banking industry. For decades, both the financial and real sides of the economy have experienced considerable consolidation. We show that banking-sector consolidation is, in part, a consequence of real-sector consolidation; because small banks are a disproportionate source of small-business credit, they are disproportionately exposed to shocks to small-business growth. Using a Bartik instrument based on national small-business trends and county-level industry exposure, we show that changes to the real-side demand for small-business credit is partially responsible for the relative decline in small banks' deposits, income, and loan growth.

Keywords: consolidation; banks; community banks; relationship lending; Bartik instrument
JEL Codes: G21, G34, L25, R12

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I. Introduction

In recent decades, the American economy has steadily consolidated, with larger firms taking an ever-increasing share in both real and financial industries, driven in part by rapid technological innovations and landmark regulatory changes. The literature shows that consolidation in the banking industry promotes consolidation in real industry,[1] which is itself associated with negative effects to labor market dynamism, mark-ups, firm entry, and product-market competition.[2] In this paper, we provide evidence that the reverse is also true and identify a new mechanism contributing to banking industry consolidation. Due to the unique relationship between small businesses and small banks, real industry consolidation depresses demand for small business loans — products for which small banks have a comparative advantage — which reinforces banking industry consolidation.

Over the last several decades, the banking industry has consolidated considerably and small banks have held a steadily decreasing share of all deposits. In 2002, banks with less than $1 billion (hereafter, small banks)[3] in assets held approximately 65 percent of all deposits in the average county. By 2017, the share of deposits held at small banks had fallen to about 50 percent. At the national level, the decline in the small-bank share of deposits has been similar in magnitude, falling from about 24 to just 10 percent. Given the outsized role that small banks play in small-business lending,[4] academics and policy-makers have expressed concern that consolidation in the banking industry has pernicious effects on small businesses and the economy more broadly. The banking literature has generally focused on exploring how changes to the financial sector have affected small firms and economic growth.[5] In this paper, we show that causality may also run in the opposite direction: industrial consolidation has led to consolidation in the financial sector. Furthermore, given banks' role as a financial intermediary between disparate sectors, and combined with existing literature, our results suggest that banks may act as a transmission mechanism for consolidation shocks between industries.

Figure 1 shows the long-term secular decline of small-firm (fewer than 250 employees) employment shares alongside the decline of small-bank (less than $1 billion in assets) deposit shares nationally from 2000 through 2017.[6] Although small-firm employment shares initially rise in the

[1]For examples, see Cetorelli and Strahan (2006) and Sapienza (2002).

[2]For examples, see Hall (2018), De Loecker, Eeckhout, and Unger (2020), Decker, Haltiwanger, Jarmin, and Miranda (2017) and Autor et al. (2020).

[3]All dollar values in the paper are expressed in constant 2002 dollars, unless otherwise noted.

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

[5]For examples, see Cetorelli and Strahan (2006) and Sapienza (2002) among many others.

[6]Some county data is not available in June 2000 (including for some entire states). These areas can be seen in Figure A.6. 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.

early 2000s, they ultimately fall by around two percentage points going into the 2008 financial crisis. During that recession, small-firm employment shares increased slightly, before continuing to decline from 2011 through 2017. Meanwhile, small-bank deposit shares have seen an uninterrupted decline throughout, falling by approximately fourteen percentage points.

Understanding banking and small business interdependencies is particularly important in the context of the COVID-19 pandemic. Given their differential funding and liquidity characteristics (Chodorow-Reich, Darmouni, Luck, and Plosser (2020)), small businesses were particularly vulnerable to the economic fallout and were hard-hit by the pandemic (Bartik et al. (2020b)). For that reason, many of the economic programs instituted by the government in response to the pandemic focused on providing support to small and medium sized firms. Research on the Paycheck Protection Program (PPP) suggests that small businesses which received support fared better (e.g., maintained higher employment, Neilson, Humphries, and Ulyssea (2020)), that existing bank customer relationships (a particular strength of small banks) were an important contributor to PPP supply (Bartik et al. (2020a) and Li and Strahan (2020)), that banks were an important part of targeting PPP funds (Granja, Makridis, Yannelis, and Zwick (2020)), and that community banks were more likely to make PPP loans (Marsh and Sharma (2021)).[7]

Our argument proceeds in three parts. First, we argue that shocks to the real economy have resulted in changes to the organizational structure of industry and, consequently, small-business loan demand. 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 (Jia (2008) and Holmes (2011)). Technological changes also contribute to consolidation in the agricultural sector, (MacDonald (2014), MacDonald, Hoppe, and Newton (2018)). Second, we rely on extensive empirical and theoretical literatures arguing that small banks' comparative advantages lie in their services to small businesses.[8] For example, small banks' flat organizational structures may provide better incentives for soft information collection for more opaque small-business loans than their large bank counterparts. Relative to large banks, a greater fraction of small-bank balance sheets is invested in small business and agricultural loans.[9] Small business performance can also affect small bank growth through other banking services, including small-business deposits (Kennickell, Kwast, and Pogach

[7]Chetty et al. (2020), Granja, Makridis, Yannelis, and Zwick (2020), and Autor et al. (2022) find that the PPP had only a modest effect on employment levels. Kapinos (2021) finds that PPP had a short-lived negative effect on small business activity.

[8]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)).

[9]As of 2002, small commercial and agricultural loans were on average 4 percent of assets for banks with more than \$1 billion in assets and 12 percent for banks with less than \$1 billion.

(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)). Finally, given the first two points, a (relative) reduction in local small business activity is expected to produce a decline in the presence of small banks relative to large banks, whose business models rely comparatively less on small businesses.

The empirical challenge in assessing the impact of shocks to small businesses on small banks is that theory and evidence suggest that shocks to small banks also affect small businesses. Technological and regulatory changes affecting small banks reduce the supply of small-bank financial services to their customers, who are disproportionately small businesses. Therefore, in estimating the effects of the *demand* for small business financial services on small banks, our strategy must account for the small bank *supply* of financial services. To resolve this challenge empirically, we rely on a Bartik instrument. Given small banks' disproportionate reliance on small businesses, we then argue that local small-firm demand shocks will affect small-banks' local presence. In our primary specification, we construct a county-year level Bartik instrument using annual national industry growth by firm size[10] 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 identifying assumption for the purposes of this paper is that this ex-ante variation does not predict innovations to small-bank financial services supply, conditional on other controls. We discuss this assumption and associated diagnostic tests suggested by Goldsmith-Pinkham, Sorkin, and Swift (2020) in Appendix A.

We find that small-business employment growth is a statistically and economically significant factor explaining small-bank deposit growth. Further, we show that medium-bank and large-bank deposit growth is not related to small-firm employment growth. Combined, the results imply that lower small-firm employment growth is associated with small banks taking a decreasing share of deposits.[11]

[10]Unless otherwise specified, we use "growth" to mean "log differences plus one" throughout the rest of the paper. Our primary hypotheses focus on the relationship between growth rates in small-business employment and growth rates in small-bank deposits, rather than levels. Considering growth (i.e., first differences) has the added benefits of addressing nonstationarity concerns if the series is $I(1)$, and, in the panel format, addressing any omitted variable bias in estimation from time-invariant variation across MSAs.

[11] We use small bank deposit growth as our outcome variable of interest rather than small bank deposit shares because it best reflects our hypothesized mechanism that small-firm demand for financial services determines the success of small banks. In contrast, small bank shares may fluctuate due to changes in the denominator even if the demand for small-bank financial services is unchanged. Thus, movement in the denominator adds unwanted noise. In addition, small bank shares are restricted to lie in the interval $[0, 1]$ and a large number of county-years have only small banks. For counties with only small banks, as small banks grow or shrink with small-firm employment, small-bank shares remain unchanged. In unreported results, we find a relationship between small-bank shares and small-firm employment shares, but the results using shares are more sensitive to assumptions and sample selection.

Across specifications, we find that a one percentage point decrease in small-firm employment growth is associated with approximately a 0.9 percentage point decrease in small-bank deposit growth. This coefficient implies that a one standard deviation increase in county-year small-firm employment growth (7.2 percentage points) is associated with a 0.28 standard deviation increase in small-bank deposit growth (6.5 percentage points). 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. Furthermore, we find that small-firm employment growth is not associated with deposit growth at medium-sized ($1 billion to $50 billion in assets) or large (greater than $50 billion) banks. This confirms our interpretation that small-firm employment is associated with bank consolidation.

We consider the intensive and extensive margins through which small-bank deposits may be affected by changes to small business employment. On the extensive margin, we examine the relationship between small-business employment growth and the propensity of small banks to be acquired, to grow through acquisition, or to exit via failure. The results demonstrate that the main findings are driven on the extensive margin primarily by the propensity of small banks to be acquired in the face of declines in small-business employment (or, in contrast, a lesser propensity to be acquired in the presence of small-business employment growth). We do not find that small banks are more likely to grow by acquiring other banks or to exit the market through failure in response to changes to small-business employment growth. The results are consistent with the view that reduced loan demand from small businesses may make economies-of-scale from a large-bank business model more profitable than a small-bank model that specializes in small-business lending. On the intensive margin, we examine within-bank deposit growth as a function of banks' exposure to small-business loan demand. We find that a one percentage point increase small-business employment growth is associated with a 0.62 percentage point increase on the intensive margin in small-bank deposits. In addition, we find that the results on the intensive margin are driven by banks with material small-business lending on their balance sheet, consistent with a relationship-lending channel. The within-bank parameter estimate is smaller than that in the baseline specification, but the estimate demonstrates that the main results are a combination of effects on both the intensive and extensive margins.

To understand the effects of changes in small business on small banks' financial conditions, we construct proxies for county-level small-bank balance sheet and income variables by apportioning small-bank financial statements to counties based upon their deposit footprints. We find that small-firm employment growth is positively associated with increased small-bank small-business lending, and commercial and industrial (C&I) loan growth, but less related to residential real estate loan growth. Furthermore, we find that small-business employment growth is positively associated with small-bank return on assets (ROA) and that this effect emanates predominantly through lower loan loss provisions.

This paper relates to research on bank consolidation, industrial sector consolidation, and relationship lending. Berger, Demsetz, and Strahan (1999) provide a summary of the literature on bank consolidation, highlighting leading theories of consolidation through the time of its publication. Among the authors' leading explanations for consolidation are increased economies-of-scale from technological innovation, international consolidation of markets, and regulatory changes. Radecki, Wenninger, and Orlow (1997) argue that the availability of alternative deposit service delivery methods (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 effects on economies of scale. In the 1990s, major legislation removed barriers to bank size, leading to arguments that bank consolidation is a direct consequence of deregulation. For instance, the Riegle-Neale Act of 1994 removed restrictions on interstate bank branches and the Gramm-Leach-Bliley Act of 1999 removed prohibitions on affiliations with certain nonbank financial intermediaries. Consistent with this theory, Jayaratne and Strahan (1998) show that the removal of restrictions on interstate branching increased bank merger and acquisitions activity. 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 smaller banks. This argument is, at least in part, the rationale behind the passage of the Economic Growth, Regulatory Relief and Consumer Protection Act of 2018.[12]

There is an extensive literature examining the causes and effects of consolidation in the real side of the economy. At the national level, Grullon, Larkin, and Michaely (2019) examine publicly traded firms in Compustat and find that large firm shares and market concentration have generally increased across industries, including the financial industry. Starting from the late 1990s, the market share for the largest four firms increased in more than 80 percent of industries, and for 21 out of 65 industries the largest four firms' collective market share increased by more than 40 percentage points. Like banks, technological advancement is a commonly cited cause of national consolidation patterns. Goldmanis, Hortascu, Syverson, and Emre (2010) argue that e-commerce contributes to decreased profitability of small firms.Meanwhile, innovations in supply chain management may support the rise of large retailers as Jia (2008) finds that Walmart entry is responsible for approximately 50 percent of the nationwide decline in small discount retailers. In addition to technological changes, the literature also points to demographic changes (Hopenhayn, Neira, and Singhania (2018)) and regulatory changes (Gutiérrez and Philippon (2017)) as possible causes of

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

real-side consolidation patterns. The effects of the real-side consolidation are also widely debated. One branch of the literature argues that real-side consolidation is responsible for increasing markups and market power (Hall (2018), De Loecker, Eeckhout, and Unger (2020)), declining labor market dynamism (Decker, Haltiwanger, Jarmin, and Miranda (2017)), and declining labor market shares (Autor et al. (2020)). However, a growing literature contests the relationship between observed national consolidation trends and product-market competition (Rossi-Hansberg, Sarte, and Trachter (2020)) by documenting the divergence of national and local consolidation patterns; Across many industries, large firms are taking a larger national market share, even as local market competition has broadly increased. In this paper, we document an additional effect of national real-side consolidation: the consolidation of the financial sector.

Our paper also fits into the more limited literature on inter-industry spill-over effects of consolidation. The Council of Economic Advisers (2016) 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 our own, uses Walmart expansion as an instrument on small-business retail. Despite different time periods and identifying assumptions, both papers find evidence that real-sector industrial organization trends have played an important role in the consolidation of the banking industry.

The literature on small "community" banks and their comparative advantage in relationship lending also informs our argument. Relationship lending refers to financial services that require investment 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 this view, 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 ability to acquire "soft" information inaccessible to large banks, community banks expand access to credit. The organizational structure typically exhibited within community banks may also 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 (see Berger and Udell (2002) and Petersen and Rajan (1995)). The flat organizational structure of community banks may also mitigate agency frictions between loan officers and management, as the close proximity of senior management and the loan officer 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." Though the comparative advantage is neither static (Berger, Cowan, and Frame (2011)) nor uniform across the industry (Federal Deposit Insurance Corporation (2018)), the literature consistently finds that small banks have a comparative advantage in serving small businesses.

II. Data

We measure small business employment using Census Quarterly Workforce Indicators (QWI) data on firm employment.[13] The QWI data provide local labor market statistics by industry and are sourced from the Longitudinal Employer-Household Dynamics (LEHD) employer and 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 firm size.[14] Note that we use firm size, rather than establishment (physical place of work) size because our narrative revolves around the premise that banking decisions are made at a firm, rather than an establishment, level. For example, as of January 2017, Target Corporation had 323,000 employees and 1,803 stores, approximately 180 employees per store.[15] We view the relevant size of Target, with regard to its choice of financial services, to be one large firm with 323,000 employees, rather than 1,803 establishments with less than 200 employees each (on average). Thus, the measure of local firm employment for a county with a single Target store assigns 180 employees to a large firm with 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, 20-49, 50-249, 250-499, and 500+ employees. Through the rest of the paper, we use these size categories to define small firms (those with fewer than 250 employees) and large firms (those with more than 500 employees), designating

[13] In Section VII, 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, the 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.

[14] There are a variety of standards used by government agencies to determine small business status. Banks most commonly rely on revenue to determine internally whether a business is small (Federal Deposit Insurance Corporation (2018)).

[15] Target Corporation, 2016 Annual Report.

firms with between 250 to 500 employees as neither small nor large.[16] We use June data from each year for all specifications to align with the timing of the branch-level deposit data, as discussed below.

Using this data, we examine both the change in employment and the change in the share of employment by small firms for a wide array of industries. Figure 2 shows the cumulative industry-level employment growth and changes in small-firm employment shares by industry (plots normalized to 0 in year 2000). 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, the share of retail employment by small firms 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 declines in overall employment, saw a slight increase in the share of employment by small-firms. Meanwhile, the industry with the largest increase in the share of employment by small-firms, Mining (NAICS 21), also saw an increase in overall employment.

For bank data, we primarily use Summary of Deposits (SOD) data and the Reports of Condition and Income (Call Reports) from the Federal Deposit Insurance Corporation (FDIC). The SOD includes bank branch-level location and deposit data. The data are collected annually, each June 30th, for all FDIC-insured institutions, which includes thrifts, but excludes credit unions. The reporting structure allows for the consolidation of deposit accounts across offices, but only within a county. In our primary analysis, we aggregate deposits to the county level by bank size for computing large- and small-bank deposits growth rates and shares. We use 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.[17] The \$1 billion cutoff for small banks is common in the literature.[18] Meanwhile, the \$50 billion definition for large banks is consistent with the Dodd-Frank Act's original threshold for enhanced prudential standards. In addition, in Section VI we apportion bank financial statements into counties based upon the bank's county deposit shares and aggregate across banks to obtain a proxy for county-level small-bank income and balance sheet measures.

Table I reports summary statistics for the main sample period, from 2003 to 2017. The annual average decline of small-bank deposit shares across counties is 62 bps, while the average decline

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

[17]As with firm size, the intermediate banks are excluded at this point to avoid a mechanical relationship. However, they are considered explicitly in Table V of Section IV.

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

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-side firms, approximately 80 percent of the decrease in small-firm employment share is accounted for by an increase in the large firm employment share (15 bps). Changes in small-firm employment and small-bank deposit shares can also be observed through growth rates. The average annual growth rate for large firms across county-years is approximately 106 bps, though only about 8 bps for small firms. Meanwhile, small-bank deposits grew by 120 percent and small bank branches shrank by 160 bps. In contrast, large bank deposits grew on average by 1,442 bps across county-years and large bank branches grew by 224 bps. Collectively, both the real-side and banking industries saw stagnant growth, if not declines, in smaller institutions and considerable growth in larger institutions.

Table I also reports summary statistics for the county-proxies for small-bank financial variables.[19] County average small-bank ROA was approximately 1.2 percent during our sample period and return on equity was about 11.4 percent. County average growth in small bank lending to small businesses declined on average by 109 bps, though C&I loans and residential real estate lending grew by 59 bps and 111 bps, respectively.[20] Regarding mergers, Table I reports the proportion of deposits in a county-year associated with the small banks that are acquired, act as an acquirer, or fail. On average, approximately 1.51 percent of deposits in a given county-year are associated with a small bank that is acquired, 1.85 percent with a small bank that acquired another bank, and 0.18 percent with a small bank that failed. Section V further discusses the merger summary statistics.

[19]Note that the sample size is somewhat smaller for these variables as ROA cannot be calculated for counties with no small banks. Here we 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 exclude 0.6 percent of observations where log differences in loan volumes are greater than 2, corresponding to a growth rate of about 650 percent or more. Results are robust to alternative restrictions on outliers.

[20]We use growth in small loans for C&I purposes plus small agricultural loans as a proxy for small business loan growth. Our results are robust to various definitions of small business loans as available from Call Reports. The results are strongest using only small loans for C&I 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 is 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.

III. Methodology

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

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

where c is a county, t is a year, y_{ct} are various bank outcomes, D_{ct} is a vector of controls, x_{ct} are real sector outcomes, and ϵ_{ct} is a structural error term.[21] In our primary analysis, we are interested in the growth of small-bank deposit as the left-hand side variable, y_{ct}, and small business employment growth as the right-hand side variable, x_{ct}. Equation 1 suffers from a classic endogeneity problem: Small business outcomes may be driven by small bank outcomes, and vice versa, which would bias 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) have an important effect on 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.[22] Namely, the Bartik instrument is constructed as:

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

where k is a vector of K total industries, G_t is a $1 \times K$ vector of national small business growth rates in year t, Z_{c0} is a $1 \times K$ vector of ex ante (i.e., year 2000) industry shares for county c. This produces a standard two-stage least squares estimation procedure, 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:

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

where D is a vector of first-stage control variables, τ and γ are parameters to be estimated, and η is an error term. As discussed in Goldsmith-Pinkham, Sorkin, and Swift (2020), the underlying identifying assumption from this approach is that the industry shares are exogenous (conditional

[21] Our primary specification is at the county-year level. In some specifications, subject to data availability, we use bank-year or bank-county-years.

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

on the controls) to innovations in the outcome variable (e.g. small-bank deposit growth). For control variables D_{ct} in the primary analysis, we use county and time fixed effects. However, in some specifications (where noted) we use year 2000 county controls, namely: the log of population, the log of income per capital, an urban indicator variable, the log number bank branches, and the small-bank deposit share. Identification in these specifications would require strict exogeneity and therefore we prefer the analysis using county-level fixed effects.

However, Adão, Kolesár, and Morales (2019) demonstrate that traditional clustering methods (e.g., by state) for Bartik designs may tend to underestimate standard errors. They argue that, because there may be dependence between residuals from unobserved shift-share components, standard methods may over-reject the null hypothesis. To address this issue, they propose measures accounting for cross-geographic correlation. Acknowledging the possible limitations of the standard methodologies, we also provide confidence intervals generated by their proposed method in results tables, reported in brackets under the traditional standard errors, where appropriate. Since our analysis uses 2-digit NAICS codes, we rely on exclusively on their small-sample methodologies. Our estimated standard errors correspond to $\hat{se}_{\beta_0=0}(\hat{\beta})$ with asymmetric confidence intervals around $\hat{\beta}$ and similarly for the IV estimate, using the notation from Adão, Kolesár, and Morales (2019).

IV. Small Bank Presence

From the existing literature, it follows that banks specializing in small business lending are disproportionately affected by shocks to small business loan demand, as small banks' comparative advantage is in small business lending. On average, small loans to businesses as a fraction of assets at small banks is twice that at other banks (as of the beginning of the sample period, 2002).[23] Collectively, these arguments and observations lead to the main hypothesis: Shocks to small business loan demand affect the aggregate presence of small banks. In this section, we test this hypothesis by using county aggregates of small bank presences. Subsequent sections examine how small business loan demand affects small-bank presence, via the intensive or extensive margins.

We first estimate OLS regressions of the relationship between small banks and small businesses. Table II shows that small bank presence, measured by aggregate county small-bank deposit growth, is correlated with our measure of small-firm employment growth. Column (1) provides the results from a univariate regression of small-bank deposit growth on small business employment growth for 2003 through 2017 and shows a statistically significant relationship at the 1 percent level. The coefficient of 0.09 implies that a 1 percent growth in county small business employment is

[23]Source: Call Reports.

associated with a 9 bps increase in small-bank deposit growth.[24] Column (2) shows that the result is similar in magnitude and significance when including county level controls from 2000, the log of population, the unemployment rate, an urban indicator variable, the log of income per capita, the log of the number of branches, and the small bank share of deposits. Of the controls, only the log of population and the small bank share of deposits are statistically significant, with a larger population and a larger share of deposits at small banks each associated with lower small-bank deposit growth. Column (3) shows that the association persists at a similar magnitude and significance when fixed effects are added.[25] One possibility is that small-bank deposits are merely related to employment, in general, rather than small business employment, in particular, and we show that this is not the case. Columns (4) through (6) show the results of a similar analysis to Columns (1) through (3), but use large firm employment growth rather than small-firm employment growth as an explanatory variable. Similarly, Column (7) shows the results of an OLS regression including both large and small-firm employment growth and that small-bank deposit growth loads only on the former. In none of the specifications is large firm employment growth statistically or economically significant in its association with small-bank deposit growth. Meanwhile, Column (8) shows that even when including contemporaneous (endogenous) macroeconomic controls, namely, county population growth and county income per capita growth small-firm employment remains a strong predictor of small-bank deposit growth.

Given the OLS results, we estimate the main specification of small-bank deposit growth on instrumented small-firm employment growth and report the results in Table III. Column (1) reports the results of an OLS regression of small-bank deposit growth on the constructed Bartik instrument. The coefficient on the Bartik instrument is 0.87 and statistically significant at one percent.[26] 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, Column (2) reports 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. Column (3) gives the results of a two stage least squares regression of small-bank deposit growth on small business

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

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

[26]We note that the order of magnitude in the coefficients is much higher using the Bartik instrument than in the OLS specifications. The implications of this observation are addressed in Table IV and the corresponding discussion.

employment growth and year 2000 controls. As with Column (1) using the Bartik instrument and OLS, the parameter estimate is approximately 0.87. Using two stage least squares with year 2000 controls and year 2000 population weights, the results in Column (4) imply that a one percentage point increase in small business employment growth is associated with a 1.5 percentage point increase in small-bank deposit growth. Column (5) reports results from a two stage least squares specification with county fixed effects, which we will hereafter refer to as our baseline specification. We find that a one percentage point increase in small business employment is associated with nearly a one (0.91) percentage point increase in small-bank deposit growth, significant at one percent. Column (6) shows that the results are robust to the addition of (endogenous) contemporaneous county macroeconomic controls (log differences in population and income per capita growth). Thus, the evidence suggests that the relationship between small-firm employment growth and small-bank deposit growth is not simply a function of broader county economic conditions.

While Columns (1) through (6) show a robust relationship between small business employment and small-bank deposits, it has thus far not been shown that small business employment is unique in this regard. To begin addressing this concern, Columns (7) and (8) use a two-stage least squares approach with year 2000 controls and county fixed effects, respectively. The results show that there is a statistical relationship between small-bank deposits and large firm employment growth, albeit of half the magnitude as the relationship between small bank and small business. Column (9) provides a similar analysis using the Bartik instruments for both small and large firm employment growth to instrument for small-firm employment growth. This regression produces a similar result to Column (6) and fails to reject the Sargan-Hansen test of over-identifying restrictions, suggesting that the over-identification restrictions are valid. Column (10) reports results from a two stage least squares regression with both the large firm and small-firm employment growth, using Bartik instruments separately constructed for the large firm and the small firm national industry employment growth. The effects of employment growth on small-bank deposits are driven specifically by small business employment growth (coefficient of 1.1 significant at the one percent level) with no statistical relationship between small-bank deposit growth and large firm employment growth. However, we note that using two endogenous variables (small and large firm employment growth) cuts the Sanderson and Windmeijer (2016) F-statistic to below the usually acceptable thresholds of Stock and Yogo (2005).

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 business employment. We hypothesize that this may be due to the instrument picking up national industry trends on small business employment in a way that the variable of interest (county-level small business employment) does not. In particular, the main specifications examine contemporaneous annual relationships between small business employment growth and small-bank deposit growth. Thus, the implicit assumption in the OLS specifications is that small business employment growth does not affect future small-bank deposit growth. In the two-stage least squares the assumption is that county-level small business employment growth is not affected by *past* national industry trends in small business employment. However, one might expect the relationships of bank variables to firm variables and firm variables to national trends to be not only within the June to June calendar year of the data, but also across years. If the variable of interest (small business employment) and our instrument exhibit different patterns over time, this may contribute to the discrepancy between the OLS and two-stage results. Table IV assesses whether differences in serial correlation contribute to the results observed in the OLS and two-stage estimates. Column (1) reports regression results of annual small business employment growth on the instrument, including four years of lags.[27] The findings show that annual small business growth is indeed correlated with lags of the instrument. That is, national industry small business employment trends, weighted by county industry shares, are correlated with local small business employment, both contemporaneously and in lags. Column (2) demonstrates that local small business employment growth exhibits negative autocorrelation (autoregressive coefficient of -0.19). In contrast, Column (3) shows that the Bartik instrument exhibits positive autocorrelation (autoregressive coefficient of 0.14). Thus, while OLS regressions with only contemporaneous small business employment growth pick up a negative correlation with lagged small business 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. For each variable, the five-year cumulative growth rates are calculated. Though the longer horizon is more consistent with the time-frames of other studies using the Bartik instrument (e.g. Autor, Dorn, and Hanson (2013)), it reduces the amount of data used for analysis by 80 percent. Nevertheless, Columns (4) through (6) of Table IV report results from OLS regressions of five-year small-bank deposit growth on five-year small business employment growth. Column (4) uses year 2000 controls, Column (5) uses county fixed effects, and Column (6) uses county fixed effects ans controls for large firm employment growth. The OLS coefficients are an order of magnitude higher than those reported in Table II. This is consistent with the annual OLS coefficient on small-firm employment growth being biased downward through its negative

[27] In unreported analysis, we also test longer lags, but do not find them to be significant.

autocorrelation. Column (7) demonstrates that the Bartik instrument using five-year national industry trends acts as a strong instrument for five-year county small business employment growth (F-statistic 52). Finally, Column 8 shows 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 the 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.

Goldsmith-Pinkham, Sorkin, and Swift (2020) (GSS, hereafter) show that estimates using a Bartik instrument can be understood as the weighted average of just-identified instrumental variables, where each industry's 2000 county share acts as its own instrument. Using the approach from GSS, we show that our analysis depends heavily on Mining, Quarrying, and Gas Extraction; Construction; and Manufacturing, with the former providing much of the variation that drives our results. Associated diagnostic tests suggested by GSS demonstrate that the industries driving our results are themselves strong instruments. In addition, to rule out that our results are completely driven by that industry, we run the analysis excluding all counties with *any* Mining, Quarrying, and Gas Extraction employment and find that parameter estimates do not change significantly, nor do they fall below conventional thresholds for statistical significance We also show that the most important industries to our analysis (as per the GSS diagnostics) are also those for which small businesses are most reliant on bank credit.

Our results establish that small-firm employment growth drives small-bank deposit growth. However, for small-firm employment to affect small-bank deposit shares it must also affect medium- and large-bank deposit growth to a lesser extent. Therefore, to connect our findings back to the consolidation patterns, we examine differences in deposit growth reactions by bank size, focusing on medium banks (assets greater than $1 billion but less than $50 billion) and large banks (assets greater than $50 billion). In Columns (1) through (3) of Table V we examine in the relationship between aggregate county deposit growth of medium-sized banks and small-firm employment growth. In each case; an OLS specification of medium-bank deposit growth on small-firm employment growth (Column 1), an OLS specification of medium-bank deposit growth on the Bartik instrument (Column 2), and a 2SLS specification of medium-deposit growth on the instrumented small-firm employment growth; we find no statistically significant relationship. Across similar specifications in Columns 4 through 6, we also find no significant relationship between large-bank deposit growth and small-firm employment growth. Thus, consistent with our proposed mechanism, small-firm employment growth disproportionately affects deposit growth of small banks.

This paper is primarily motivated by the consolidation in the banking industry. A distinct, but related, concept surrounds bank competition. Although often used interchangeably, in our analysis the distinction is important. For this paper, we define "consolidation" as the agglomeration of economic activity from smaller firms to larger firms. We measure this concept using 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, we use HHI as a measure of market concentration. While consolidation and concentration are clearly related concepts, they may exhibit materially different properties. HHI is defined for a given geographical market, while firm size is defined independent of the geographical market. 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 the level of competition of the banking sector in that area.

To see the distinction, Figure 3 plots the average county HHI and small bank shares from 2000 through 2017. Whereas for the average county, small-bank deposit shares monotonically decreased since the turn of the century, the 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 net change in market concentration, the set of banks competing in the average county shifted away from smaller institutions. The finding is similar to that of Rossi-Hansberg, Sarte, and Trachter (2020), who show that national consolidation patterns have not generally led to decreased local product-market competition.

Columns (7) through (9) of Table V report the results of an OLS regression of changes in county deposit HHI on our variable of interest, small business employment growth, and show no relationship between real-side small business dynamics and local bank competition. Similarly, we find no effect of small-firm employment growth on competition (HHI) using an OLS specification with a Bartik instrument or a 2SLS specification. The results of Table V establish that small-firm employment affects local banking markets primarily by changing the competitiveness of small banks, but without much affect on medium- or large-banks or the overall competitiveness of the local banking market.

V. Extensive vs. Intensive Margin

Our baseline results suggest that local small-firm employment affects local small-bank presence. In this section we examine the mechanisms that contribute to the result. Given our definition of "small" banks as those below \$1 billion, the county-level small bank measurements can be affected by small business employment growth through at least four distinct mechanisms. Small banks could be acquired by larger banks, ceasing to be "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; that is, grow by expanding their business rather than aquiring another bank. Our paper relies on the view that small banks have a comparative advantage in small business lending. If small businesses struggle, then a small bank cannot capitalize on their comparative advantage in small business lending. 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 business customers would be unlikely to capitalize on their comparative advantage through acquiring another institution. While it seems theoretically possible for small business employment to affect small-bank deposits and branches through failure, we expect that failures are more likely the consequence of larger regional and macroeconomic trends or idiosyncratic events (e.g., fraud). Alternatively, small banks might organically grow – or shrink – with the successes and failures of local small businesses. In this section, we explore how small businesses affect small bank presence on the extensive and intensive margins.

A. Extensive Margin

To examine the mechanisms through which small-bank deposit growth may occur on the extensive margin, we isolate the changes to small-bank deposits from acquisition,[28] acquiring another institution, and failing. The analysis described below demonstrates that on the external margin, the results are driven by a higher propensity of small banks to be acquired when small business employment declines. Using the same Bartik estimation strategy, we study the extent to which each of these exit types is affected by small business employment growth. However, mergers and failures happen at a bank level, not at 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. That is, when a bank merges, the relative impact on deposits of that merger is distributed to counties proportionally, based on the holdings of that bank in each county. Approximately 1.5 percent of deposits in an average county-year are associated with an acquired small bank, 1.9 percent of deposits are associated with an acquiring small bank, and approximately 0.2 percent are associated with a failed small bank.

Table VI shows the relationship between acquired, acquiring, and failed small banks to small

[28]Intra-company mergers are excluded in our merger definition, where an "intra-company" acquisition is defined as a merger in which the institutions involved belonged to the same holding company for more than one year prior to the merger.

business employment growth. To remain consistent with the baseline specification, the table reports results using OLS and 2SLS frameworks.[29] Columns (1) through (3) report the results of regressions of acquired small-bank deposits to total county deposits. Columns (1) and (2) show a strong statistical relationship between small business employment growth and acquired small-bank deposits, using county controls and county fixed effects, respectively. Increased small business employment is associated with less acquired small-bank deposits. Column (3) shows that the relationship continues to hold using the 2SLS specification. In Columns (4) through (6), we define $AcqHQ = 1$ if there is small bank headquartered in the county acquired during the year and zero otherwise. Columns (4) and (5) show a strong statistical relationship between small business employment growth and acquired small-bank deposits, using county controls and county fixed effects, respectively. Increased small business employment is associated with a lower propensity for a bank headquartered in the county to be acquired. Finally, Column (6) demonstrates that the relationship again holds using the 2SLS 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, there is no statistically significant relationship. Columns (9) through (10) report the results of regressions of small-bank deposits associated with a failed small bank to total county deposits. Again, both with county controls and county fixed effects, there is no statistically significant relationship. Thus, the results are driven by the higher propensity of small banks to be acquired when small business employment declines or, alternatively, the lower propensity of small banks to be acquired when small business employment increases.

B. Intensive Margin

To what extent are the results driven by the effects of local small business employment on individual small banks? One way to answer this question is to examine a bank-specific exposure to firm employment growth by firm size. To do this, we restrict the sample to banks that were "small" in the prior year that were also not involved in a merger, thereby allowing banks to remain in the sample in the year that they grow out of the small definition. For each bank-year, we weigh the county-year measures by the county-share of deposits for the bank in the prior year, thus creating a by-bank measure of industry exposure.

Table VII shows that the county-level relationship carries through to the bank level. That

[29] In unreported analysis, results are of similar statistical significance using tobit specifications as to what is reported in Table VI. However, because county fixed effects cannot be used in a tobit specification, we opt to report only results using linear regression models.

is, small-firm employment growth affects small-bank deposit presence on the intensive margin. Columns (1) through (3) provide the direct bank-level analogue to the OLS regression results in Table II and the baseline results in Table III. Columns (1) and (2) show that the OLS estimates yield a positive, significant relationship between small business growth and bank-level deposit growth, whether or not large-firm employment growth is taken into account. Column (3) provides the 2SLS estimate of the same relationship using the Bartik instrument. In all three cases, the magnitudes are similar to the baseline county-level results.

Using within-bank variation, we also explore whether the results are consistent with the hypothesized small business credit channel. If the positive effect of small businesses on small banks flows through the small firm's demand for credit services from small banks, we would expect to see a weaker relationship for small banks which are less heavily reliant on commercial lending. Consequently, we split our sample banks' based upon the extent of their small-business lending operations as a ratio of total assets, as of the year 2002: those banks that hold a material amount of small-business loans (at least five percent of their assets) and those that do not.[30] The results, shown in Table VII Columns (4) through (8), show that deposits at small banks that are relatively more (less) reliant on small-business loans have a stronger (weaker) relationship with small-firm employment growth. Column (4) provides the result of an identical regression to Column (2), restricted to those banks that do not have a meaningful small-business lending portfolio (i.e., small-business loans are less than five percent of their assets). We find that there is no statistical correlation between small-firm employment growth and small-bank deposit growth for small banks not engaged in small-business lending. Furthermore, in Column (5), we find that for small banks not engaged in small-business lending, the relationship between large-business employment growth and small-bank deposit growth is similar in magnitude to the relationship between small-business employment growth and small-bank deposit growth, with the former significant at the ten percent level and the latter insignificant.

In contrast, Columns (6) and (7) provide identical analysis to Columns (4) and (5), but restricted to those banks with at least five percent of their assets held in small-business loans. Similar to the baseline results, small-firm employment growth is strongly associated with small-bank deposit growth for those small banks with material small business lending portfolios, with or without controlling for large-firm employment growth. Finally, in Column (8) we show using 2SLS that the bank-level results are driven by those banks with material small-business lending activities. Combined, the results show that the intensive margin result is dependent on banks that more heavily rely on small-business lending, consistent with a credit channel mechanism.

[30]The results are robust to other thresholds of materiality for small-business lending.

VI. Effects on Small Bank Balance Sheets and Incomes

While the SOD data allows for measurement of small-bank deposits, it is also of interest to understand how small-firm employment affects small-bank balance sheets and income statements beyond deposits. However, data by bank-county for those variables do not exist, precluding direct measurement. In this section we construct county-level small-bank balance sheets to illuminate to the effects of small-firm employment on small banks more broadly.

For each variable of interest w_{it} (e.g. net income or C&I loans) for bank i at time t, the consolidated value is apportioned into county c according to the share of deposits held in that county. [31] That is:

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

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

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

With this measure of county-specific bank portfolios, we can delve more deeply into the effects on specific loan types. Table VIII reports the results of OLS regressions and the baseline 2SLS regressions with county fixed effects using the proxies for aggregate small bank lending. Columns (1) through (3), use growth in small bank small agricultural and small C&I loans (often used as a proxy for small business loans) as the independent variable, in Columns (4) through (6) use growth in total C&I loans, and in Columns (7) through (9) use growth in residential real estate loans. Column (1) shows that small commercial and agricultural loan growth at small banks is strongly related to small business employment. Column (2) shows that small commercial and agricultural loan growth remains related to small business employment growth, even after controlling for large-firm employment growth, which is not significantly related. Column (3) provides a two-stage regression which shows that small business employment 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 business employment, but not large-firm employment, is related to small-bank C&I loans. Moreover, Column (6) shows that much of the increase in small bank commercial loans from increased small business employment can be accounted for by small loans (0.83 of 0.93). For all specifications in Column (1) through (6), the parameter estimates

[31] The analysis remains consistent with the SOD timing and use data as of June. For flow variables, this requires a four quarter lagged summation.

on small bank loan growth resemble those of similar specifications of small-bank deposit growth reported in Table III. Columns (7) and (8) show only a weak statistical relationship between small-firm employment growth and small-bank residential real estate lending in OLS regressions, again suggesting that small business credit is the main channel. 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 Column (6). This is also 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)).

Income statement items can be similarly attributed at the county level for each bank. In Table IX, we report results from OLS regressions and the baseline 2SLS regressions with county fixed effects using the county proxies for small-bank income statement variables. Columns (1) through (3) report regressions using net income relative to assets as the independent variable. The regression results provided in Columns (4) through (6) instead use net income relative to equity. Finally, the results reported in Columns (7) through (9), shows the relationship between loan loss provisions (as a portion of assets) and small business employment. Columns (1) and (2) show that small-firm employment is strongly related to small bank performance, as measured by return on assets (ROA). Column (2) demonstrates that large firm employment growth is also strongly correlated with small bank ROA, albeit the parameter estimate is an order of magnitude smaller than for small business employment. Column (3) reports a 2SLS approach with the Bartik instrument. It shows that small business employment is associated with ROA, significant at the one percent level. Thus, when small business employment growth is higher, local small banks see a significantly higher return on assets. The coefficient of 0.024 in Column (3) implies that a one standard deviation increase in small business employment growth (7.2 percent) is associated with approximately an 18 bps increase in small-bank ROA, equal to about 14 percent of average small bank ROA (or a 0.12 standard deviation increase in small-bank ROA). Columns (4) through (6) report similar specifications to Columns (1) through (3), except using return on equity rather than ROA. The results are qualitatively similar to the ROA specifications, though large firm employment growth is only marginally significant in Column (5). The next few columns, (7) through (9), show that the results from the other columns are largely driven by loan loss provisioning. That is, much of the additional income banks see comes through reduced provisions on expected loan losses. Columns (7) and (8) show that small business employment growth is associated with decreased loan loss provisions (of similar magnitude to the increase ROA). 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 business employment. Finally, Column (9) shows that a one standard deviation increase in small-firm employment growth leads to a 9.5 bps reduction in loan loss provisions relative to assets, equal to approximately 22 percent of the mean, or a 0.13 standard deviation decrease in loan loss provisions to assets.

VII. Small Business Loan Demand

Our analysis relies on small business employment as a measurement of small business demand for financial services. Identification, as discussed in Section III, requires that industry shares are exogenous (conditional on the controls) to innovations in the outcome variable (e.g. small-bank deposit growth). Yet, even if one accepts identification, we still must establish that our variable of interest, small-firm employment growth, captures small-firm demand for financial services.

In this section, we assess the relationship between small-firm employment and small-business loan demand using small business lending data from the Community Reinvestment Act (CRA). The CRA was intended to encourage depository institutions to help meet the credit needs of the communities in which they operate and collect deposits, including low- and moderate-income neighborhoods. The associated data is commonly used in the literature as a proxy for small-business lending (e.g., Cortés et al. (2020) and the references therein).

As a tool to measure small business loan demand, the CRA data has a number of important advantages and disadvantages. First, CRA data measures loan number and volume by bank at a county-year level. This allows us to control for bank-level loan supply using bank-year fixed effects. In addition, the CRA data measures small loan volumes by firm size. In particular, we observe the volume of small loans originated to firms with less than \$1 million in gross revenue.[32] While restricting attention to firms with less than \$1 million in gross revenue allows us to exclude small loans to large businesses, the reporting requirements of CRA do not allow us to capture the approximately 20 percent of small business loans originated with more than \$1 million (Federal Deposit Insurance Corporation (2018)). We account in part for small-business loan measurement issues resulting from the loan size restrictions by incorporating bank-year and county fixed effects, recognizing that accurate measurement of small-business loans remains a challenge. Another disadvantage of using CRA data is that it does not cover the universe of banks. In particular, banks with less than \$1 billion (real 2005) do not report CRA data. For the purposes of our study, the asset size threshold is not ideal, since it does not allow us to capture the small-business loans at small banks and so requires the assumption that small business loan demand at small banks is correlated to small business loan demand at larger banks. However, notwithstanding the absence

[32] While loan size is often used as a proxy for small businesses, Federal Deposit Insurance Corporation (2018) finds that this measure has notable weaknesses and is not consistent with banks' definitions of small businesses (see also Goldston and Lee (2020)).

of small banks in the CRA data and measurement challenges associated with loan size, we note that multi-county, typically larger, banks are valuable for establishing the link between small-firm employment growth and small business loan demand, as the multi-county banks allow the inclusion of bank-year fixed effects to control for loan supply.

Table X examines county small business lending growth within bank-years as a function of small business employment growth. The results demonstrate a strong relationship between small business loan origination and small business employment. In each specification, we include bank-year fixed effects to account for bank-specific credit supply and restrict attention to county-years with at least ten observations to minimize endogeneity of county small-firm employment outcomes from bank-specific credit supply, though results are not sensitive to that threshold.

Columns (1) through (4) show that small business employment growth is correlated with small business loan growth, where loan volumes are measured as originations to firms with less than $1 million in revenue. Using county controls, a one percent increase in small-firm employment is associated with a 13 bps increase in small-business lending, with (Column (1)) our without (Column (2)) the inclusion of large firm employment growth. We find similar results when including county fixed effects. Notably, county-level large firm employment growth is not associated with small-business loan demand, suggesting that small-firm employment growth is not simply picking up on county-year specific macroeconomic conditions that are also consistent with large-firm employment growth. We find similar results in Columns (3) and (4) using county fixed effects and in Columns (5) through (8) defining small businesses as those with less than $250 thousand in revenue.

VIII. Conclusion

For decades, consolidation has been a dominant trend in industries as diverse as agriculture, manufacturing, pharmaceuticals, and retail. The banking industry is no exception; the number of small banks has steadily decreased, while the largest firms control an ever-increasing market share. We argue that the dramatic consolidation of the financial industry is at least partly a *consequence* of consolidation on the real side of the economy. Small banks disproportionately rely on small businesses as a core part of their business model. As firms in real industries consolidate, due to technological advancement, economies of scale, or monopolistic rents, the smaller firms that form the foundation of small banks' relationship-lending business model gradually disappear. With fewer borrowers, small banks face a lower demand for their relationship-based loan products, leading to a reduced small bank presence. Viewed alongside existing literature on how bank consolidation affects the supply of small-business credit, our results suggest that banks may act as a cross-industry transmission mechanism of industry-specific consolidation patterns.

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 6 to 7%. This relationship extends to the lending side of the balance sheet, as well. Decreases in small business 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.

Taken in the context of existing literature's conclusion that bank consolidation reduces small-business lending, our results suggest a possible consolidation feedback loop between the real and financial sectors of the economy. The ongoing viability of small banks may depend on the ongoing viability of small businesses. Many long-term and emergency support programs (like the PPP) seek to support small businesses via small banks, but our results suggest that the converse may be a viable approach, as well. If policy makers wish to support small, local, community banks, supporting small business may be an effective 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: Multivariate OLS regressions of small bank deposit growth. Columns (1) through (3) report regression results of county-level small-bank deposit growth on small-firm employment growth using year fixed effects only, year-fixed effects plus year 2000 county controls, and year fixed-effects plus county-fixed effects, respectively. Columns (4) through (6) report regression results of county-level small-bank deposit growth on large-firm employment growth using year fixed effects only, year-fixed effects plus year 2000 county controls, and year fixed-effects plus county-fixed effects, respectively. Errors clustered at the state level. Columns (7) reports regression results of county-level small-bank deposit growth on small-firm employment growth and large-firm employment growth, using year and county fixed effects. Column (8) reports regression results similar to Column (7), adding contemporenous macroeconomic controls of population growth and income per-capita growth. Errors are 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)			
urban_{2000}		-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	YES	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 III: 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) reports results from an 2SLS regression of log differences in small-bank deposits on log differences in small-firm employment instrumented with 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. Column (10) reports results from an 2SLS regression of log differences in small-bank deposits with two endogenous variables, log differences in small-firm employment and log differences in large-firm employments instrumented with both two Bartik instruments. 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(SmDp)	Δln(SmDp)	Δln(SmDp)	Δln(SmDp)	Δln(SmDp)	Δln(SmDp)
$Bartik_{small}$	0.868***	1.061***								
	(0.193)	(0.207)								
	[0.547, 1.315]	[0.625, 1.784]								
$\Delta ln(\widehat{SmEmp})$			0.869***	1.505**	0.906***	0.812***			0.855***	1.137***
			(0.164)	(0.690)	(0.176)	(0.180)			(0.158)	(0.395)
			[0.545, 1.310]	[0.388, 1.320]	[0.550, 1.559]	[0.487, 1.519]				
$\Delta ln(\widehat{LgEmp})$							0.365***	0.447***		-0.220
							(0.101)	(0.0889)		(0.268)
							[0.146, 0.535]	[0.143, 0.670]		
$\ln(pop_{2000})$	-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)			
$SmDp_{2000}$	-0.0297***		-0.0286***	-0.0324*			-0.0298***			
	(0.00594)		(0.00616)	(0.0190)			(0.00604)			
Δln(inc)						0.00512				
						(0.0396)				
Δln(pop)						-0.182***				
						(0.0590)				
Observations	36,117	36,574	36,069	36,069	36,525	36,068	36,069	36,525	36,525	36,525
R-squared	0.011	0.060								
REG	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
F-stat			56.8	127	65.4	88.5	122.1	67.6	57.8	4
J-stat									1.1	
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 IV: 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	$\Delta\ln(\text{SmEmp})_{1yr}$	$\Delta\ln(\text{SmEmp})_{1yr}$	Bartik_{1yr}	$\Delta\ln(\text{SmDp})_{5yr}$	$\Delta\ln(\text{SmDp})_{5yr}$	$\Delta\ln(\text{SmDp})_{5yr}$	$\Delta\ln(\text{SmDp})_{5yr}$	$\Delta\ln(\text{SmDp})_{5yr}$
Bartik_{1yr}	1.295***							
	(0.180)							
L.Bartik_{1yr}	0.198*		0.142***					
	(0.115)		(0.00650)					
L2.Bartik_{1yr}	0.125							
	(0.117)							
L3.Bartik_{1yr}	0.296**							
	(0.136)							
L4.Bartik_{1yr}	0.305**							
	(0.137)							
$\text{L.}\Delta\ln(\text{SmEmp})_{1yr}$		-0.192***						
		(0.0191)						
$\Delta\ln(\text{SmEmp})_{5yr}$				0.408***	0.395***	0.406***		0.547**
				(0.105)	(0.0629)	(0.104)		(0.262)
								[0.065, 4.673]
Bartik_{5yr}							0.967*	
							(0.565)	
							[-0.309, 5.903]	
$\Delta\ln(\text{LgEmp})_{5yr}$						0.00833		
						(0.0201)		
Observations	31,132	36,456	36,494	7,150	7,061	7,150	7,167	7,106
R-squared	0.138	0.146	0.936	0.316	0.050	0.316	0.308	0.048
F-Stat								90.4
REG	OLS	OLS	OLS	OLS	OLS	OLS	OLS	2SLS
F-Stat								85.0
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
COUNTY FE	YES	YES	YES	YES	NO	YES	YES	YES
CONTROLS	NO	NO	NO	NO	YES		YES	NO
YRS	2006-2017	2003-2017	2003-2017	2003-2017	2003-2017	2006-2017	2003-2017	2003-2017

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

Table V: Regressions of log differences medium-bank deposits, log differences large-bank deposits, and change in deposit HHI on log differences in small firm employment. Columns (1)-(3) report results from regressions of log differences in medium-bank deposits on small firm employment growth (OLS), the Bartik instrument using exposure to national trends in industry small-firm employment growth (OLS), and small firm employment growth instrumented with Bartik instrument (2SLS), respectively. Columns (4)-(6) report results from regressions of log differences in large-bank deposits on small firm employment growth (OLS), the Bartik instrument using exposure to national trends in industry small-firm employment growth (OLS), and small firm employment growth instrumented with Bartik instrument (2SLS), respectively. Columns (7)-(9) report results from regressions of changes in county-deposit HHI on small firm employment growth (OLS), the Bartik instrument using exposure to national trends in industry small-firm employment growth (OLS), and small firm employment growth instrumented with Bartik instrument (2SLS), respectively. Errors clustered at the state level are reported in parentheses, below which appear 95 percent CIs using Adão, Kolesár, and Morales (2019) with the null imposed.

		Δln(MedDep)			Δln(LgDep)			ΔDepHHI	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta ln(SmEmp)$	0.0376		0.0427	0.0170		0.115	-0.0032		-0.0277
	(0.0275)		(0.216)	(0.0119)		(0.118)	(0.0032)		(0.0391)
			[-1.61, 0.60]			[-0.26, 0.64]			[-0.06, 0.07]
Bartik_{small}		0.0509			0.138			-0.0326	
		(0.272)			(0.143)			(0.0511)	
		[-1.76, 0.77]			[-0.32, 0.75]			[-0.08, 0.08]	
Observations	35,131	35,131	35,131	35,582	35,582	35,582	36,069	36,069	36,069
R-squared	0.062	0.062	0.013	0.106	0.106	0.023	0.057	0.057	-0.000
REG	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS
F-stat	N/A	N/A	66	N/A	N/A	66.9	N/A	N/A	66.5
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 VI: 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	AcqDep	AcqDep	AcqDep	AcqdHQ	AcqdHQ	AcqdHQ	BuyerDep	BuyerDep	FailDep	FailDep
Δ ln(SmEmp)	-0.0293***	-0.0311***	-0.221***	-0.0567**	-0.0662***	-0.330*	0.0120	0.0121	-0.00613	-0.00709
	(0.00904)	(0.00992)	(0.0666)	(0.0212)	(0.0200)	(0.173)	(0.00912)	(0.00891)	(0.00475)	(0.00578)
			[-0.58, -0.12]			[-0.83, -0.09]				
ln(pop_{2000})	0.00145			0.0141*			-0.00414**		0.000668	
	(0.00136)			(0.00725)			(0.00183)		(0.000835)	
$unemp_{2000}$	-0.000468			0.00138			-0.000908**		8.97e-05	
	(0.000447)			(0.00188)			(0.000394)		(0.000145)	
$urban_2000$	0.00195			0.0416***			-0.000802		0.00188	
	(0.00141)			(0.00898)			(0.00283)		(0.00152)	
ln($income_{2000}$)	0.00309			0.0686***			-0.00384		-0.000229	
	(0.00310)			(0.0184)			(0.00329)		(0.000919)	
ln(br_{2000})	-0.00145			0.0527***			0.00430**		-0.000733	
	(0.00142)			(0.00882)			(0.00188)		(0.000967)	
$SmDep_{2000}$	0.0162***			0.0607***			0.0212***		0.00144	
	(0.00184)			(0.0120)			(0.00216)		(0.00107)	
Observations	33,660	33,660	33,660	33,660	33,660	33,660	33,660	33,660	33,660	33,660
R-squared	0.008	0.083		0.100	0.213		0.013	0.122	0.013	0.094
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
F-stat			67.1			67.1				

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

Table VII: Regressions of growth in bank-level deposits on employment growth. Columns (1) and (2) report the OLS bank-level results controlling for small firm employment only and for small and large firm employment, respectively. Column (3) reports the results from 2SLS regressions of bank-level deposit growth on the instrumented small business employment growth, using exposure to national trends in industry small business employment growth and on large firm employment growth instrumented using exposure to national trends in industry large-firm employment growth. Columns (4) and (5) report the OLS bank-level results for only those banks with less than five percent of their assets held in small business loans, without an with controlling for large firm employment growth, respectively. Columns (6) and (7) report the OLS bank-level results for only those banks with more than five percent of their assets held in small business loans, without an with controlling for large firm employment growth, respectively. Column (8) reports the results from 2SLS regressions of bank-level deposit growth for only those banks with five percent or more of their assets held in small business loans instrumented small business employment growth, using exposure to national trends in industry small business employment growth. Errors clustered are at the bank level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$\Delta\ln$(Dep)	$\Delta\ln$(Dep)	$\Delta\ln$(Dep)	$\Delta\ln$(Dep)	$\Delta\ln$(Dep)	$\Delta\ln$(Dep)	$\Delta\ln$(Dep)	$\Delta\ln$(Dep)
$\Delta\ln$(SmEmp)	0.0805***	0.0822***	0.618***	0.0304	0.0336	0.0940***	0.0954***	0.597***
	(0.0117)	(0.0118)	(0.103)	(0.0331)	(0.0335)	(0.0115)	(0.0116)	(0.0868)
$\Delta\ln$(LgEmp)		0.0120***			0.0200*		0.0100***	
		(0.00343)			(0.0112)		(0.00355)	
Observations	66,748	66,748	66,585	16,921	16,921	49,827	49,827	49,723
R-squared	0.188	0.188		0.188	0.188	0.190	0.190	
REG	OLS	OLS	2SLS	OLS	OLS	OLS	OLS	2SLS
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	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
F-stat			158.9					152.5

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

Table VIII: 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Δln(SmSBLoan)	Δln(SmSBLoan)	Δln(SmSBLoan)	Δln(SmCI)	Δln(SmCI)	Δln(SmCI)	Δln(SmRE)	Δln(SmRE)	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)	(0.238)	(0.0208)	(0.0209)	(0.233)	(0.0212)	(0.0212)	(0.227)
$\Delta ln(\widehat{LgEmp})$		-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
F-stat			136.3			136.3			136.3
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 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ROA	ROA	ROA	ROE	ROE	ROE	Prov	Prov	Prov
$\Delta ln(SmEmp)$	0.00551***	0.00539***	0.0268***	0.0654***	0.0665***	0.281***	-0.00463***	-0.00473***	-0.0151**
	(0.00159)	(0.00156)	(0.00845)	(0.0182)	(0.0184)	(0.0861)	(0.00103)	(0.00104)	(0.00719)
$\Delta ln(LgEmp)$		0.000441*			0.00587**			-0.000528***	
		(0.000224)			(0.00222)			(0.000150)	
	(0.000596)	(0.000563)		(0.00697)	(0.00697)		(0.000301)	(0.000301)	
Observations	35,068	34,653	35,064	35,068	35,068	35,064	35,068	35,068	35,064
R-squared	0.497	0.498	0.186	0.477	0.477	0.183	0.461	0.461	0.307
REG	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS
F-stat			80.40			80.4			80.4
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 X: Small Business Loan Demand. Columns (1) through (4) define small business as those with revenues less than $1 million. Columns (1) and (2) report results from an OLS regression of log changes of small business loan volume at the bank-county-year level on county-year small-firm employment growth using bank-year fixed effects and county controls from 2000. Columns (3) and (4) report results from an OLS regression of log changes of small business loan volume at the bank-county-year level on county-year small-firm employment growth using bank-year fixed effects and county fixed effects. Columns (5) through (8) repeat the analyses of Columns (1) through (4) defining small businesses as those with revenues less than $250 thousand. All specifications restrict to county-years with at least 20 bank observations. Errors are double clustered at the county and bank levels.

	$ Originated, Small Bus w/ Revenue < $1m				$ Originated, Small Bus w/ Revenue < $250K			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Δ Ln(SBLoans)	Δ Ln(SBLoans)	Δ Ln(SBLoans)	Δ Ln(SBLoans)	Δ Ln(SBLoans)	Δ Ln(SBLoans)	Δ Ln(SBLoans)	Δ Ln(SBLoans)
$\Delta ln(SmEmp)$	0.132***	0.134***	0.104***	0.105***	0.147***	0.148***	0.126***	0.126***
	(0.0295)	(0.0298)	(0.0301)	(0.0305)	(0.0270)	(0.0273)	(0.0276)	(0.0280)
$\Delta ln(LgEmp)$		0.0126		0.00704		0.00683		0.00136
		(0.0102)		(0.0103)		(0.00935)		(0.00948)
ln(pop_{2000})	0.0151***	0.0150***			0.0155***	0.0154***		
	(0.00465)	(0.00463)			(0.00485)	(0.00484)		
$unem_{2000}$	-0.00379***	-0.00377***			-0.00298***	-0.00297***		
	(0.000897)	(0.000896)			(0.000879)	(0.000878)		
$urban_{2000}$	0.0128***	0.0127***			0.0123***	0.0123***		
	(0.00337)	(0.00338)			(0.00314)	(0.00315)		
ln($income_{2000}$)	0.00281	0.00271			0.0103	0.0102		
	(0.00747)	(0.00747)			(0.00675)	(0.00675)		
ln(br_{2000})	-0.00348	-0.00334			-0.00451	-0.00444		
	(0.00381)	(0.00381)			(0.00401)	(0.00401)		
$SmDep_{2000}$	-0.00556	-0.00558			-0.00128	-0.00129		
	(0.00615)	(0.00615)			(0.00562)	(0.00561)		
Observations	705,112	705,112	705,112	705,112	705,112	705,112	705,112	705,112
R-squared	0.180	0.180	0.182	0.182	0.206	0.206	0.208	0.208
REG	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Bank-YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
COUNTY FE	NO	NO	YES	YES	NO	NO	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

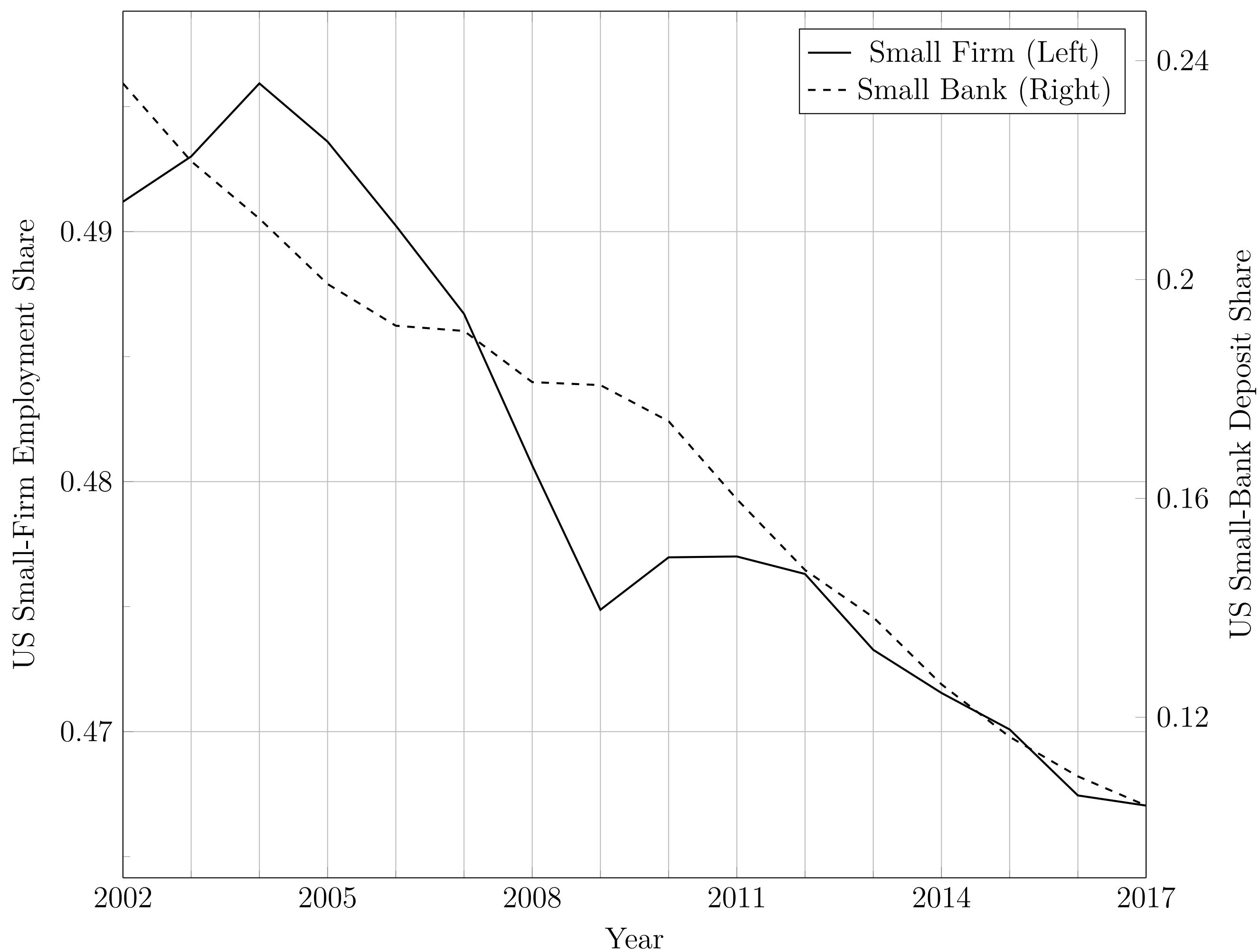

Figure 1: Source: Census Quarterly Workforce Indicators (Firm Shares). FDIC Summary of Deposits (Deposit Shares). Small Firms are defined as those with fewer than 250 employees. Small banks are defined as those with less than $1 billion in assets (constant 2010 dollars).

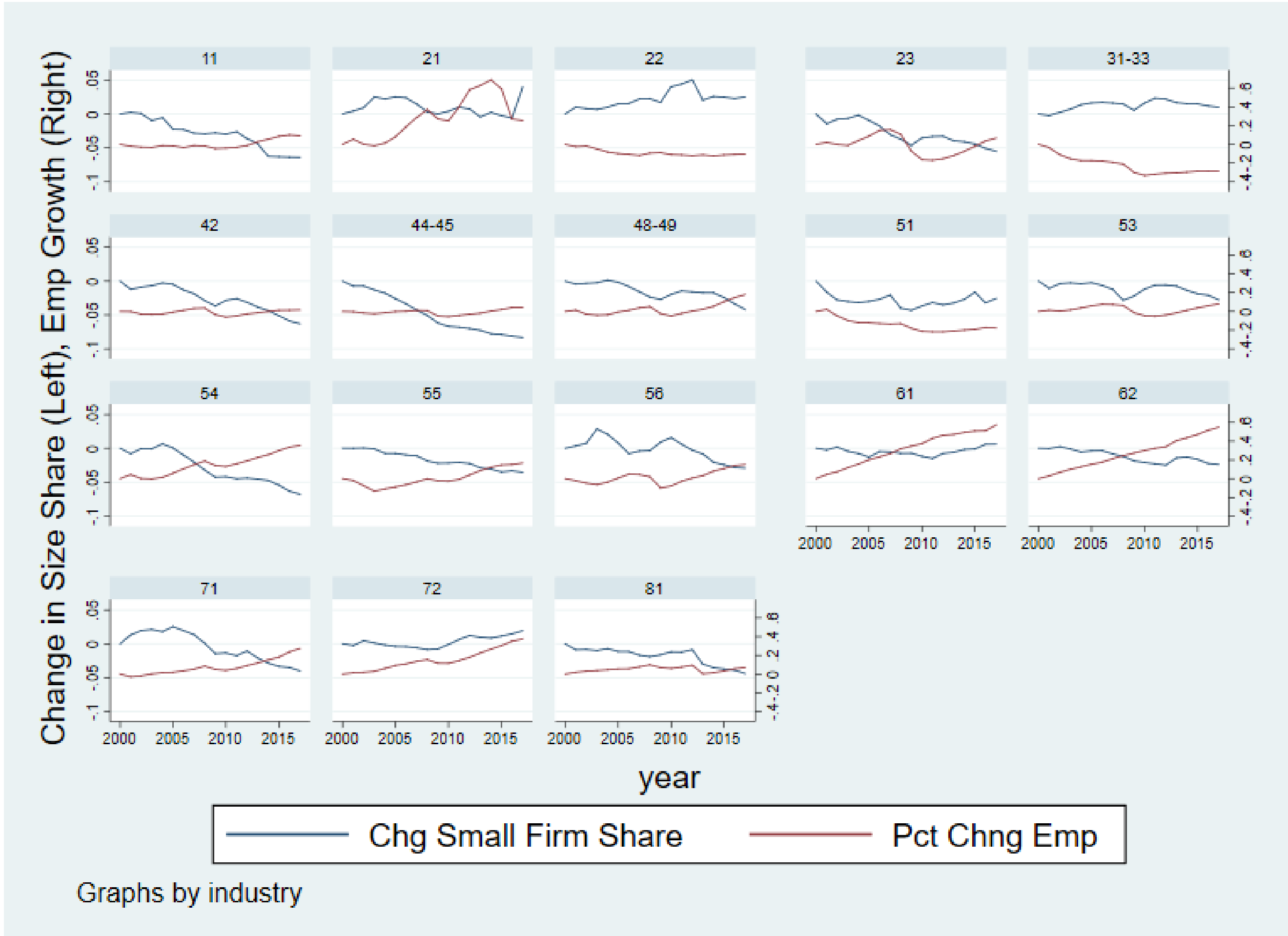

Figure 2: Source: Census Quarterly Workforce Indicators (Firm Shares). Small Firms are defined as those with < 250 employees. Sector 11: Agriculture, Forestry, Fishing and Hunting. Sector 21: Mining, Quarrying, and Oil and Gas Extraction. Sector 22: Utilities. Sector 23: Construction. Sector 31-33: Manufacturing. 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.

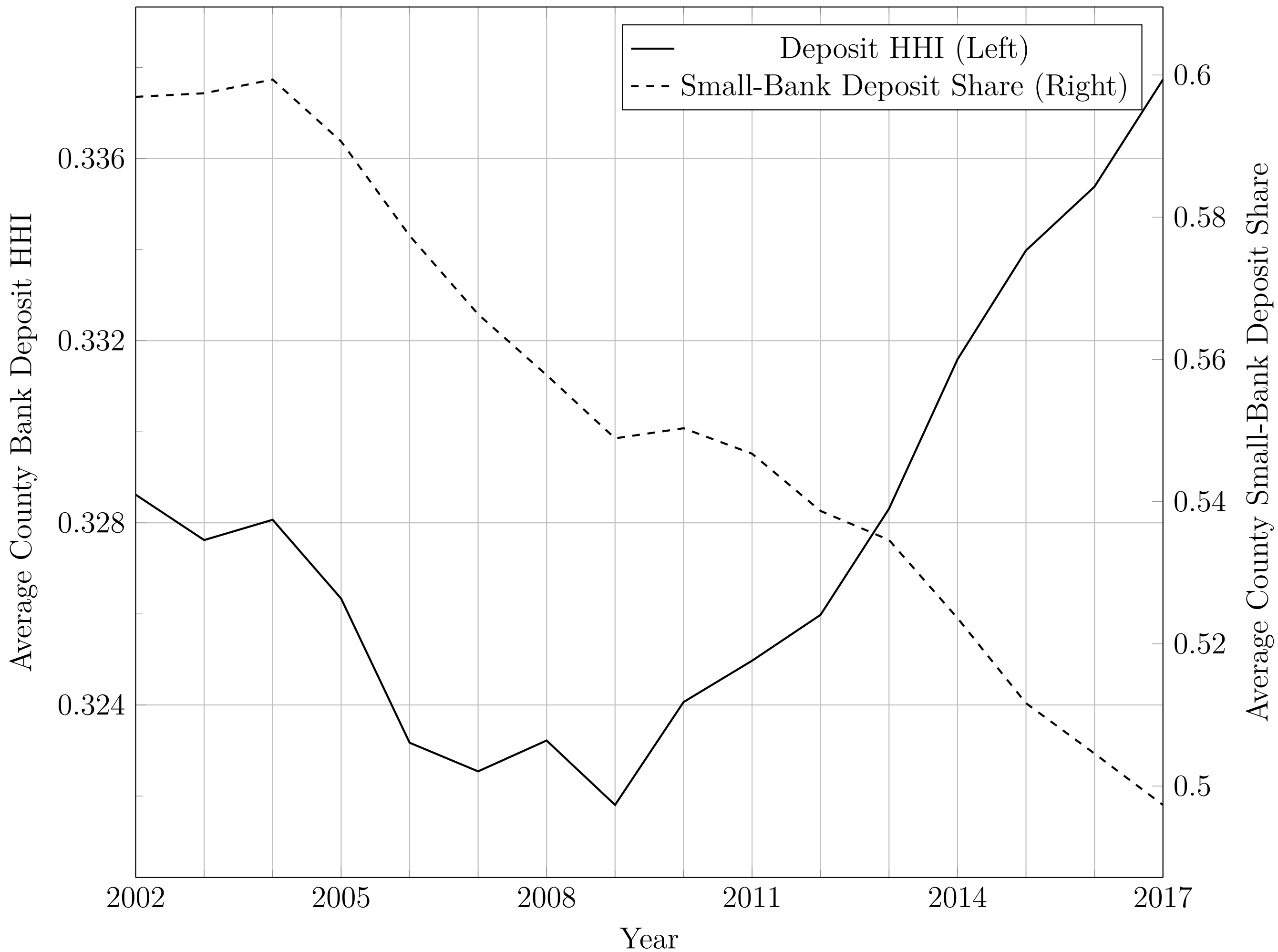

Figure 3: Source: Summary of Deposits. Small banks are defined as those with < \$1 billion in assets.

For Online Appendix

Appendix A Bartik Diagnostics

The identification of the estimates depend critically on the validity of the Bartik instrument, which can be difficult to assess as the inner product of county-industry shares and national industry growth rates. Thus, to examine the credibility of the instrument, we rely heavily on the recent work of Goldsmith-Pinkham, Sorkin, and Swift (2020) (GSS, hereafter). In particular, GSS discuss the construction of Rotemberg weights, which allows better understanding of the primary industries driving the estimates and makes the set of specification tests supporting the research design more concrete. In this section, we provide the Rotemberg weights associated with our instruments and discuss the implication of those findings to our main results.

GSS show that the Bartik instrument is 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

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

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

where Z_{kc0} are year 2000 county c shares of industry k, g_{kt} is the national small firm growth rate of industry k in year t demeaned by the industry average,[33] X is a matrix of county small-firm employment growth rates, Y is a matrix of small-bank deposit growth rates, and $X^\perp = M_D X$. Here, M_D is the annihilator matrix for control vector D, $M_D = I - D(D'D)^{-1}D'$, and I is the identity matrix. For simplicity of notation, hereafter denote $\hat{\alpha}_k = \sum_t \hat{\alpha}_{kt}$.

The Bartik instrument reflects variation in 2000 county-industry shares. Thus, we must 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 underlying assumptions of exogeneity are most critical to the empirical design or, in other words, the assumptions for which the research design is most sensitive to mis-specification. In Table A.11 and Figures A.4 and A.5, we report the diagnostics of the Bartik instrument as suggested by GSS.

Panel A of Table A.11 shows that the bulk of the absolute weight of the estimator is absorbed by industries that receive positive weights. According to GSS, since the weighted sum of the

[33] 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.

negative instruments is relatively low, it is less likely that the negative weights on β_k are critical to the overall estimate. Panel B shows that industries that recieve a higher weight 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-stage F-statistics, an observation that is also borne out in Figure A.4. This is an important diagnostic, as it reveals that the high-weight industries act as strong instruments. In addition, higher weights are associated with industries displaying more share variation across counties (correlation coefficient 0.450). Panel C demonstrates that much of the absolute weight of the instrument is absorbed by two years in the data: 2009 and 2016. Of course, 2009 marked the nadir of the Great Recession, but the importance of 2016 is less clear. Panel D of Table A.11 indicates that, consistent with Figure A.4 the top five industries absorb nearly the entirety of the absolute weight of the estimator. Moreover, the top two industries (Mining, Quarrying, and Gas Extraction; and Manufacturing) receive more than 70 percent of the estimator's absolute weight.[34]

Thus, our identifying assumption can be best understood as an assumption that, conditional on other covariates, ex-ante county-level employment shares for these two industries are not driven by future innovations to small-bank deposit growth, especially for 2009 and 2016. For example, a critical assumption is that the share of a given county's employment from mining was not dependent on new deposit growth at small banks 9 and 16 years later in the same county. Panel D provides 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 intervals generally overlap (with manufacturing being the one exception). Thus, individual industry shares that are important to the main findings provide similar, if noisy, estimates.

To understand the context behind the relationship between small banks and small businesses in these particular industries, particularly in the ex-ante period (year 2000), we consider the 1998 Survey of Small Business Finances (SSBF), from the Board of Governors of the Federal Reserve System. With this nationally representative sample, we observe how many firms in a particular industry use bank services, and which services they use. While the SSBF uses SIC codes, rather than NAICS, their categories overlap enough to make a meaningful comparisons possible. Firms within the categories "Construction and Mining" and "Primary Manufacturing", generally similar to the three industries receiving the highest Rotemberg weights in our analysis, used credit significantly more frequently than small businesses in general ($p < 0.001$). In 1998, 67 percent and 57 percent of "Construction and Mining" firms and "Primary Manufacturing" firms, respectively, used credit lines, loans, or capital leases, compared to 55 percent of all firms. In fact, firms in "Mining", the most important industry to our analysis, were more likely to use any such credit service than firms in every other industry ($p < 0.001$). By 2003, 71 percent and 70 percent of "Construction and Mining" and "Manufacturing" firms used one of these credit services, compared to 60 percent of small firms overall. Besides credit relationships, 88 percent of "Construction and Mining" firms and 90 percent of "Primary Manufacturing" firms used some service provided by a

[34] Given the large weight on "Mining, Quarrying, and Gas Extraction", in unreported analysis, we ran the baseline specification excluding any counties reporting any employment in that industry. 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.

commercial bank, qualitatively similar to the 89 percent of all small business that use such services.

Estimates across industries are not identical. To illustrate the heterogeneity in the just-identified instruments, Figure A.5 plots the first-stage F-statistics against the just-identified estimators β_k. We restrict attention to only those instruments with material first-stage power (those 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. The size of the shapes of the markers reflect the magnitude of the weight $\hat{\alpha}_k$. Similar to Panel D in Table A.11, the plot demonstrates that the strongest first-stage industries in the analysis produce estimates similar to the overall Bartik estimator (i.e. centered around 0.9). However, we note that some of the industries with lower Rotemberg weight and F-statistics produce more varied estimates of β.

Counties with relatively high shares of employment in the most important industries will have an outsized importance in the estimates. Figure A.6 highlights 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 A.11. We note strong concentrations in Nevada, western North Dakota, and western Texas, consistent with the importance of Mining, Quarrying, and Gas Extraction. However, other counties with high industry shares appear to be widely distributed across the United States.

As mentioned above, analysis of the Rotemberg weights from the baseline regressions shows that “Mining, Quarrying, and Gas Extraction, Construction”, and “Manufacturing” provide most of the variation upon which the instrument relies. To better understand how the instrument relies upon these industries, we run a similar analysis using 3-digit NAICS codes. In general, the results are similar to those presented above, though the first-stage F-statistics are slightly weaker. Nevertheless, the exercise allows us to better understand the industries that drive our parameter estimates. Table A.12 reports the Rotemberg weights for the baseline specification (small-bank deposit growth on small business employment growth with county fixed effects) using three-digit NAICS codes. Similarly to the case with two-digit NAICS codes, the estimates are primarily driven by Mining, Quarrying, and Gas Extraction, Construction, and Manufacturing. Support Activities for Mining (NAICS 213) accounts for the bulk of the weight among those in the broader industry classification (NAICS 21) and Oil and Gas Extraction (NAICS 211) accounts for the majority of the remainder. The small business share of employment for these industries are 40.7 and 28.7 percent, respectively. Within Construction, the bulk of the Rotemberg weights are driven by Specialty Trade Contractors (NAICS 238), an industry dominated by small firms, accounting for 82.6 percent of industry employment. Wood Product Manufacturing (NAICS 321), where small businesses account for 50.3 percent of employment, drives the weight in Manufacturing. In each case, the just-identified parameter estimates are statistically greater than zero, ranging from 0.38 to 1.2. Forestry and Logging (NAICS 113) has the fifth largest Rotemberg weight, though the parameter estimate has the opposite sign.

Table A.11: 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 A.12: 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

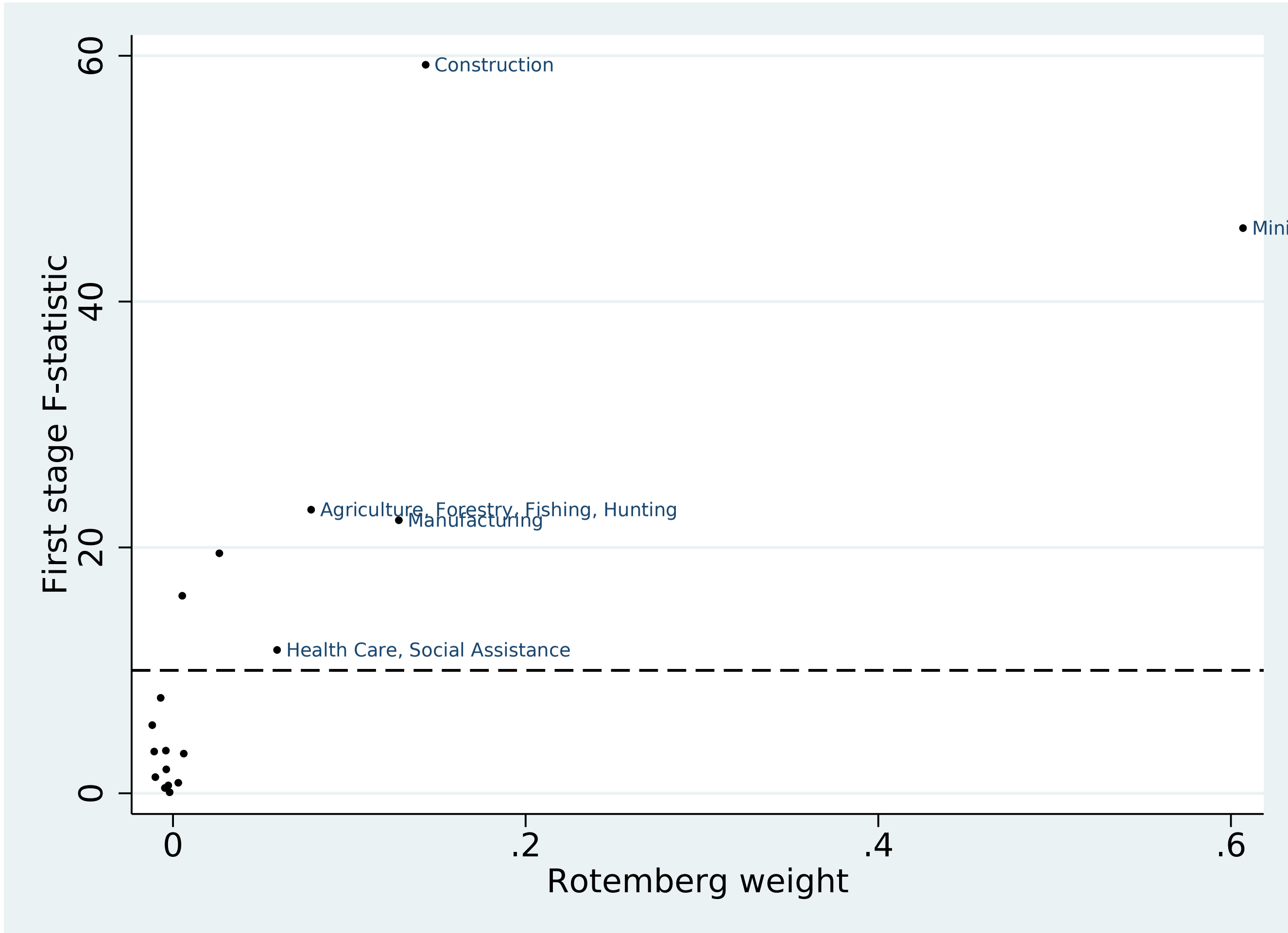

Figure A.4: This figure plots the relationship between each instruments' β^k, first stage F-statistics and the Rotemberg weights. Each point is a separate instrument's estimates (industry share). The figure plots the estimated β^k for each instrument on the y-axis and the estimated first-stage F-statistic 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.

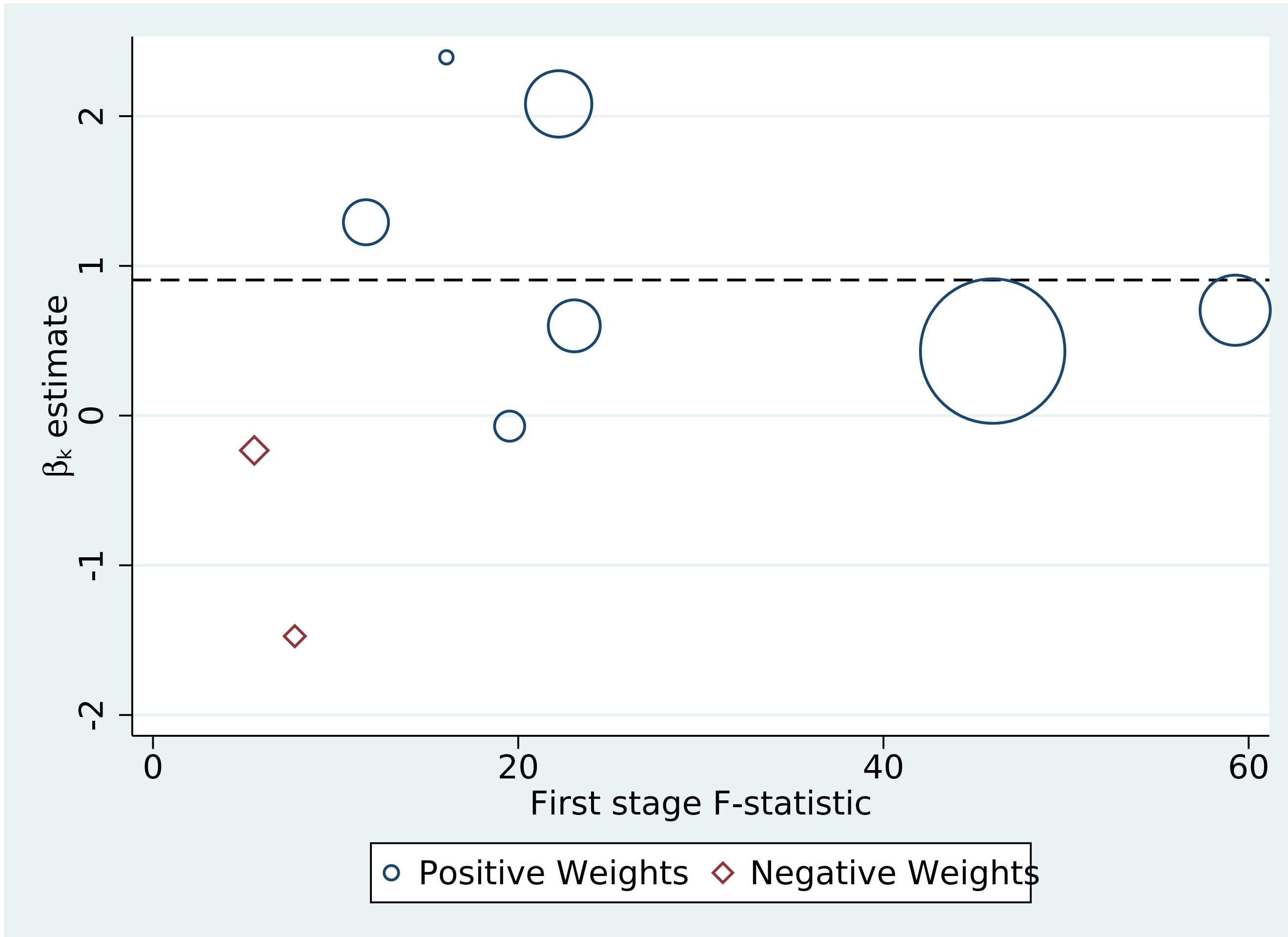

Figure A.5: Heterogeneity of Just-Identified County-Share Instruments

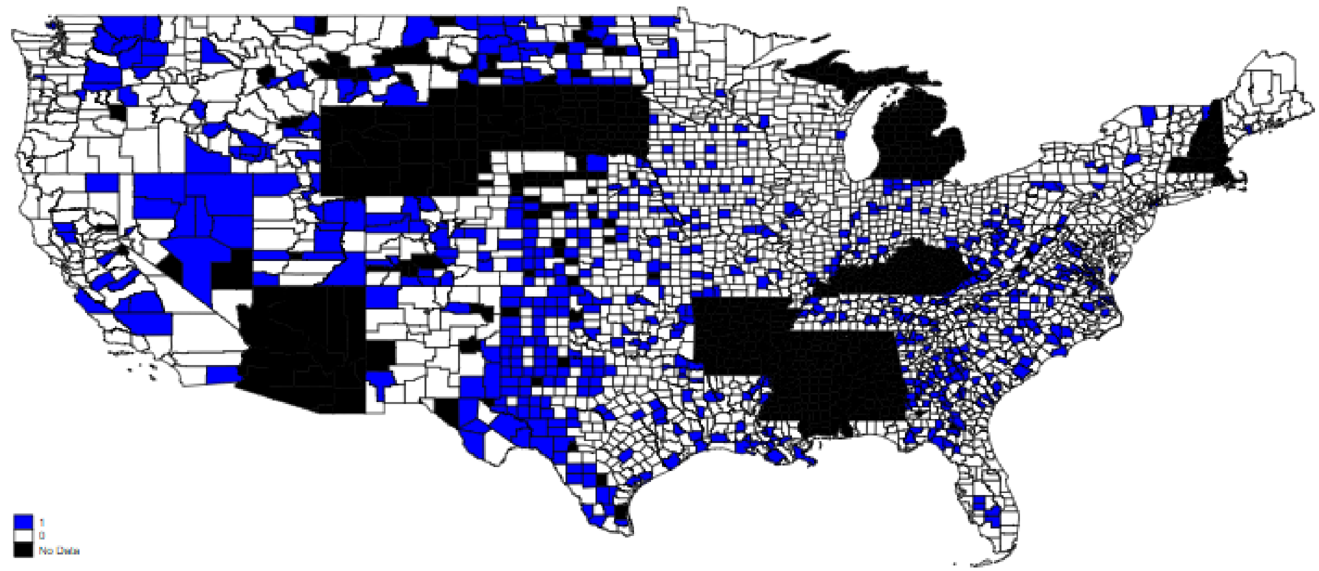

Figure A.6: Source: Census QWI. Counties labeled with a “1” lie in the 95th percentile or higher of year 2000 county-industry shares for at least one industry with a Top 5 Rotemberg weight according to Table A.11 and those labeled with a “0” lie below the 95th percentile of year 2000 county-industry shares for all industries with Top 5 Rotemberg weights.