# Local Financial Structure and Economic Resilience

Ross Levine, Chen Lin, and Wensi Xie†

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**Abstract**

Does the structure of the financial system influence the economy's resilience to adverse shocks? Using high-frequency, U.S. county-level data on employment, small business revenue, and COVID-19 cases, we discover that employment, especially the employment of low-income workers, and the revenues of small firms fall by less in response to local COVID-19 cases in counties with a larger proportion of small banks. Furthermore, small banks increase lending to small businesses more than large banks in response to the pandemic. Using QWI data, employment of small firms falls less by less in response to COVID-19 cases in counties with a larger proportion of small banks. Evidence suggests that small banks provide funding to small firms following an adverse shock, with positive repercussions on employment.

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† Corresponding author, Levine: Haas School of Business, University of California, Berkeley. Email: rosslevine@berkeley.edu.
Lin: Faculty of Business and Economics, University of Hong Kong. Email: chenlin1@hku.hk.
Xie: CUHK Business School, Chinese University of Hong Kong. Email: wensixie@cuhk.edu.hk.

## 1. Introduction

A defining feature of financial systems is the extent to which they provide funding to firms to make positive net present value (NPV) investments (Myers and Majluf 1984; Fazzari, Hubbard, and Petersen 1988; Levine 1997). The ability of financial systems to fund such investments and provide immediate liquidity is especially important when adverse shocks temporarily reduce the profitability of firms (Bernanke, Gertler, and Gilchrist 1999; Acharya and Steffen 2020). Without access to finance, more firms will reduce employment, magnifying the impact and transmission of the shock.

Small firms and banks may play a key role in this nexus between financial constraints, employment, and the propagation of shocks. Besides employing almost half of all private-sector workers and more than half of low-income workers (Acs and Nichols 2007; Small Business Administration 2020), research suggests that small firms are often more opaque and hence subject to tighter financing constraints than larger firms (Petersen and Rajan 1994; Berger and Udell 1998; Beck, Demirgüç-Kunt, and Maksimovic 2008). As a result, it might be especially difficult for small firms to obtain countercyclical financing, increasing the severity of recessions. Research further suggests that small banks have a comparative advantage over large banks in augmenting the use of "hard" information that is contained in financial and accounting statements with "soft" information that is acquired through the establishment of long-term relationships with businesses, where this soft information is often crucial for evaluating and financing small businesses (Berger and Udell 1995, 2002; Canales and Nanda 2012; Berger et al 2005, 2020; Berger, Goulding, and Rice 2014; Berger, Bouwman, and Kim 2017). These findings raise a key question: Do small banks foster economic resilience through countercyclical lending to small firms that limits reductions in employment, especially among low-income workers?

In this paper, we provide new evidence on whether and how the proportion of small banks operating in a local economy influences the economy's resilience to adverse shocks. As an adverse shock, we use cross-county differences in weekly COVID-19 infection rates across the

United States. To gauge economic resilience, we focus on how total employment and the employment of low-, medium, and high-income workers in each county respond to local COVID-19 infection rates. We focus on employment both because of the direct welfare implications of employment reductions and the role of employment reductions in magnifying and propagating adverse shocks. We focus on how the proportion of small banks operating in a county differentially shapes employment reductions across low-, medium-, and high-income workers because understanding the connections between financial structure and income distributional effects of adverse shocks is valuable for formulating sound policies. Thus, we use the pre-pandemic period as a benchmark and evaluate how local employment responds to the pandemic as a function of the proportion of small banks operating in the county. Besides employment, we examine an additional implication of the view that small banks have a comparative advantage in lending to small local businesses during the COVID-19 crisis: small local firms will be better positioned to maintain their operations and revenues in response to the pandemic in communities with a higher proportion of small banks. Finally, we examine a direct mechanism linking small banks to local employment and small firm revenues. We assess how small bank lending to small firms responds to local COVID-19 cases.

In particular, we address three questions concerning the relation between small banks and the resilience of local economies to COVID-19. First, in response to COVID-19, does employment—especially the employment of low-income workers—fall by less in counties with a higher proportion of small banks? To the extent that small banks have a comparative advantage in ameliorating information asymmetries and financing small firms following adverse shocks, the pandemic should have a more muted impact on employment in counties with a higher proportion of small banks. Furthermore, since small firms disproportionately employ low-income workers, we assess whether the employment of low-income workers falls by less in counties with a larger share of small banks. That is, we test whether small banks shape the income distributional effects of an economic crisis. Although past work explores the connection between overall financial development and the amplitude of business cycle fluctuations (Bernanke, Gertler, and Gilchrist

1999; Smets and Wouters 2007; Gilchrist and Zakrajšek 2012; Brunnermeier and Sannikov 2014), we examine how small banks influence changes in both aggregate employment and the employment of low-, medium-, and high-income workers following the economic disruptions triggered by COVID-19. Furthermore, as emphasized above, past work suggests that small banks have a comparative advantage in forming lending relations with and funding small firms and research also indicates that these lending relationships may be especially important following adverse shocks because economic downturns often intensify informational frictions (Bolton, Freixas, and Gambacorta 2016; Beck et al. 2018). We contribute by examining the degree to which small banks cushion the impact of an adverse shock on total employment and the distribution of employment across low-, middle-, and high-income workers.

Second, do the revenues of small firms fall by less in response to COVID-19 in counties with higher proportions of small banks? If small banks have a comparative advantage in financing small firms during economic downturns, then small firms should perform better in economies with a higher proportion of small banks than in counties dominated by larger banks. While past work examines how securities markets, banks, and access to trade credit shape the financing and performance of large, publicly-traded firms (Demirgüç-Kunt and Maksimovic 1998, 2002; Levine, Lin, and Xie 2016, 2018), we assess the extent to which small banks ease the impact of economic crises on the performance of small firms.

Third, how do small and large banks change their lending to small firms in response to the pandemic? As emphasized above, existing research examines the comparative advantages of small banks in funding small firms and Berger et al (2020) explore the connection between lending relationships and loan contract terms during the COVID-19 pandemic. We contribute to this research by examining how a bank's lending to small firms changes in response to the bank's exposure to COVID-19 while differentiating banks by size. In this way, we assess the differential degrees to which smaller and larger banks provide financing to small local firms following an adverse shock.

To assess the relation between small banks and how employment and the distribution of employment respond to COVID-19 infection rates, we begin by using ordinary least squares (OLS) and then employ an instrumental variable (IV) strategy. In these analyses, we use weekly observations on U.S. counties from February through June 2020. We examine total employment, unemployment insurance claims, and the employment of low-, middle-, and high-income workers. We use two measures of the proportion of small banks in a county: the share of total branches in a county that are branches of small banks and the share of total deposits in a county held in the branches of small banks. A bank is defined as "small" if its total assets are below $1 billion at the close of 2019. To measure the county's exposure to the pandemic, we use *ln(cases per capita)*, which equals the logarithm of one plus the cumulative number of confirmed COVID-19 cases per 100,000 people.

In these county-week analyses, we regress the five employment measures on *ln(cases per capita*), the proportion of small banks, and the interaction between *ln(cases per capita*) and the proportion of small banks. In this way, we assess how the relationship between employment and the adverse shock of COVID-19 varies across local economies with different proportions of small banks. To condition out all time-invariant county traits and all time-varying state influences, including state-specific social distancing orders, we include county and state-week fixed effects. Furthermore, to control for the possibility that other county-level traits besides the share of small banks influence the relation between employment and the intensity of infection rates in the county, we control for the interaction between *ln(cases per capita*) and (a) the total number of bank branches per capita, (b) income per capita, (c) the percentage of people over the age of 65, (d) population density, and (e) the pre-pandemic unemployment rate. In addition, we show that the results are robust to controlling for national policies that may influence lending to small firms and local employment, e.g., the CARES Act's Paycheck Protection Program (PPP).[1] Specifically, we condition on the cumulative amount of PPP loans per capita in each county over

[1] Compared with large corporations that have access to alternative sources of external finance (e.g., Acharya and Steffen 2020; Ellul, Erel and Rajan 2020), small firms rely more heavily on bank lending (Lin 2020).

time. Thus, in these initial analyses, we use OLS and control for a broad array of factors to limit concerns that some omitted county-specific factor besides the share of small banks shapes the local economy's resilience to COVID-19 cases.

We discover that employment—especially the employment of low-income workers—falls by less in counties with a greater share of small banks in response to COVID-19 cases. In particular, we find that aggregate employment falls by less and unemployment insurance claims increase by less in response to COVID-19 among counties with a greater share of small banks. We also uncover strong results regarding the income distributional implications of small banks. In response to COVID-19 infections, we find much smaller declines in the employment of low-income workers—but not smaller declines in the employment of middle- or high-income workers—in counties with a higher proportion of small banks. This finding is consistent with the view that small banks shape the income distributional effects of the economic disruptions triggered by COVID-19.

Next, we use the same methodology to examine whether—and show that—the revenues of small firms fall by less in response to COVID-19 in counties with a larger proportion of small banks. The dependent variable is *Small business revenue*, which equals the percent change in seasonally adjusted net revenues for small businesses in each county relative to its pre-pandemic level. The intensity of a county's COVID-19 infection rates, *ln(cases per capita)*, tends to reduce small business revenues, but *Small business revenue* falls by less in response to the pandemic in counties with higher small bank shares. These findings are consistent with the view that small banks have a comparative advantage in financing small firms during crises and this funding allows those small businesses to operate more effectively, generating greater revenues, during these periods of economic duress.

To enhance identification, we reassess the findings on employment and revenues using an IV strategy. Despite the extensive controls used in OLS analyses, there could be omitted county-specific features that are correlated with the local share of small banks, and these omitted features, not the share of small banks, could influence cross-county changes in employment and revenues in response to COVID-19 cases. Thus, we use an instrumental variable to identify the impact of the share of small banks on cross-county responses to the pandemic. The instrument equals the number of mergers by out-of-state banks that affect branch structure in a county during the decade from 2010 through 2019, where both the acquiring and target banks have at least one branch located in the county prior to the merger. Specifically, for a county *c* located in state *s*, the merger involves two banks that are not headquartered in state *s*, where each bank has at least one branch in county *c*. Such mergers will tend to give the consolidated bank a competitive advantage, reducing the role of small banks in the county. This is what we find: the merger instrument is negatively associated with the share of small banks. The identifying assumption is that the merger decision of two banks headquartered in states different from county *c* during the 2010-2019 period does not reflect local conditions that drive the county's resilience to the 2020 pandemic.

The IV results confirm all of the OLS findings: a larger share of small banks in a county mitigates the adverse shock of COVID-19 on employment, especially the employment of low-income workers, and on the revenues of small businesses within the county. In terms of instrument validity, the data reject the null hypothesis that the excluded instruments do not account for cross-county variations in the share of small banks.

Next, we use cross-sectional analyses to evaluate the connection between changes in a bank's lending to small firms and the exposure of its business clients to COVID-19. To measure the exposure of a bank's business clients to the economic duress triggered by COVID-19, we build on research showing that banks tend to make loans to small businesses that are geographically very close to their branches (e.g., Nguyen 2019). In particular, we first measure a county's exposure to COVID-19, *ln(cases per capita)*, as the logarithm of one plus the number of confirmed COVID-19 cases per 100,000 people. Second, to measure the exposure of a bank's business clients to COVID-19, we compute the weighted average of *ln(cases per capita)* across counties in which the bank has branches, where the weights are the shares of deposits held by the bank in those counties. We call this measure *Bank exposure*. We define small business loans as loans with origination values of $1 million or less following the classification of Community Reinvestment Act (CRA) and measure changes in a bank's lending to small firms using the growth in the dollar amount of loans to small businesses. We consider two other measures of credit supply, overall C&I loan growth and PPP loans. *C&I loan growth* equals the log difference between commercial & industrial loans between Q2-2020 and Q4-2019 for each bank. *PPP loans* equals the amount of PPP loans outstanding as of Q2-2020 scaled by total assets as of Q4-2019. According to Li and Strahan (2021), bank credit supply through the CARES Act's Paycheck Protection Program (PPP) accounts for a major of bank loans during first few months of 2020. We then regress the three measures of small business loan growth on *Bank exposure*, while controlling for each bank's size, liquid assets, equity ratio, tier 1 ratio, NPL, ROA, and the U.S. state in which it is headquartered.

We find a positive relation between a bank's growth in lending to small firms and *Bank exposure* among smaller banks but not among larger banks. We measure the differences between smaller and large banks in two ways: using a discrete cutoff, where banks with less than $1 billion of assets are defined as "small" and all other banks are defined as "large," and using a continuous measure of bank size. The findings from both approaches indicate that smaller banks increase lending to small firms more than larger banks during the pandemic. These cross-sectional analyses are consistent with the view that small banks have a comparative advantage in funding small firms during periods of economic duress. The results hold when examining *C&I loan growth* and *PPP loans*. This is consistent with the findings in Li and Strahan (2021), which stresses a new benefit of bank relationships: small banks prioritize serving their relationship borrowers during the Covid crisis, facilitating small firms to access government-subsidized lending.

Finally, we evaluate whether employment at small firms falls by less in response to local COVID-19 cases in areas with a larger share of small banks. The LEHD Quarterly Workforce Indicators (QWI) database provides granular employment data at the county, two-digit NAICS sector, and firm size groups, allowing us to distinguish employment by firm size. The frequency of the QWI data is quarterly, not weekly. The effects of the share of small bank on employment are more pronounced among small firms. This is consistent with the notion that that small banks provide liquidity to small firms during periods of economic duress, mitigating the adverse effects of the Covid-19 pandemic on employment.

Our work relates to a growing body of research on the linkages between financial and markets. Beck, Levine, and Levkov (2010) find that regulatory changes that improved bank lending boosted the demand for labor, especially the demand for low-income workers, reducing income inequality. Focusing on the 2008-9 financial crisis and the relationship between syndicated lenders and large firms, Chodorow-Reich (2014) shows that firms that had pre-2008 relationships with syndicated lenders that were more severely hurt by the 2008-9 financial crisis reduced employment by more following the onset of the crisis than otherwise similar firms with pre-crisis connections to syndicated lenders that were less adversely affected by the crisis. Giroud and Mueller (2016) show that establishments of more highly levered firms experienced larger employment losses in response to drops in local consumer demand during the great recession. Exploiting stock market fluctuations, Lin (2020) shows that stock market booms reduce household demand for demand deposits, and the deposit outflows induce banks to cut lending, leading to contractions in local employment. Focusing on the bank lending channel, Brown and Earle (2017) find that relaxing credit constraints on small firms tend to increase employment, but Greenstone, Mas, and Nguyen (2020) challenge these results, finding that the bank lending channel did not have material effects on employment following the 2008-9 financial crisis tightened credit constraints. Our research and contributions are distinct. Rather than focusing on the ramifications of shocks to bank lending in general or the syndicated lenders in particular, we examine how the structure of local banking markets shapes the resilience of local employment, the structure of local employment across low-, medium-, and high-income workers, and the revenues of small local firms to the COVID-19 pandemic. We discover that a larger share of small banks in a county cushions the impact of COVID-19 cases on employment, especially the employment of low-income workers, and on the revenues of small local firms.

Our research also relates to studies on bank financing and resilience to shocks. For example, Chen, Hanson, and Stein (2017) show that large banks, especially the top-four banks, cut lending to small businesses more than other banks during the 2008 financial crisis and were slow to resume small business lending during the post-crisis recovery. Related studies investigate the role of bank lending in how economies recover from natural disasters, such as hurricanes (Schuwer, Lambert, and Noth 2019) and floods (Koetter, Noth, and Rehbein 2020). Different from these studies, we examine the ramifications of the COVID-19 pandemic that many influential economists describe as very different from the past crises (e.g., Bernanke 2020; Reinhart 2020). For example, the 2020 pandemic was at its core a public health emergency that triggered an abrupt constriction in economic activity and an especially severe decline in employment, whereas the GFC arose from concerns about overall financial system stability and the safety of individual banks. In light of these differences, our research offers the first investigation of the role of local bank structure in shaping economic resilience to the COVID-19 pandemic by exploiting high-frequency, real-time data on employment and other economic indicators.

## 2. Data, Summary Statistics, and Graphical Analyses

### *2.1 The Economic Tracker database*

We use a new public database, the Economic Tracker ("the Tracker" henceforth), that tracks daily economic activity at the county level. The data are compiled by Chetty, Friedman, Hendren and Stepner (2020) and the Opportunity Insights Team. The Tracker reports daily statistics on employment rates, small business revenues, and COVID-19 infection rates. Chetty et al. (2020) (1) smooth high-frequency fluctuations by reporting 7-day moving averages, (2) smooth lower-frequency seasonal fluctuations by normalizing each week's value in 2020 relative to the corresponding values for the same week in 2019, and (3) report statistics in the form of percentage changes relative to January 2020, as opposed to raw values, to protect the privacy of businesses and their clients. Finally, to construct representative series and mitigate selection biases, they compare each time series to national benchmarks and exclude data sources that do not track corresponding benchmarks closely. We now describe each data series used in our study, where each series is defined as a percentage deviation from the level in January 2020.

*2.2 Employment and unemployment claims*

Employment data are compiled by combining employment and earnings information from four complementary data sources: Paychex, Intuit, Earnin, and Kronos. Paychex collects paycheck data through offering payroll services to 670,000 small- and medium-sized businesses across the U.S., accounting for 10% of U.S. private-sector workers. Chetty et al. (2020) convert these paycheck data into employment estimates (i.e., the number of paid employees). Similarly, Intuit provides payroll services to one million businesses, through which they estimate employment data. Both Paychex and Intuit provide a firm-based payroll dataset. As a complement, Earnin provides a worker-level sample that records individual workers' earning of income. Chetty et al. (2020) construct the employment series by converting these paycheck data into employment measures. Kronos offers workforce management service to 30,000 firms which employed a total of 3.2 million workers before the pandemic. The employment data are derived from electronic timesheets on which employees clock into work.

Our sample of employment comprises 17,536 county-week observations over the period from February through June of 2020, involving 800 counties. *Employment* is the employment level for all workers relative to January 2020 at the county-level. As shown in Table 1, the average *Employment* equals -10%, suggesting that the employment rate fell by an average weekly rate of 10% over the period from February through June of 2020.

The Tracker also provides disaggregated employment series by income quartile, allowing us to evaluate the differential effects on workers in different income groups. In particular, *Employment, low income workers* represents the employment level for workers in the bottom quartile of the income distribution (incomes approximately under $27,000). *Employment, middle income workers* represents the employment level for workers in the middle two quartiles of the income distribution (incomes approximately $27,000 to $60,000). *Employment, high income workers* represents the employment level for workers in the top quartile of the income distribution (incomes approximately over $60,000).

We also examine unemployment insurance claims as a robustness check. Data on unemployment benefits are constructed using public data sources including the Department of Labor and state government agencies. *Unemployment insurance claims* equals the total number of initial claims divided by the 2019 labor force (in 100 people).

### *2.3 Small business revenue*

The Tracker provides daily data on small business revenues at the county level. In particular, *Small business revenue* equals the seasonally adjusted net revenue of small businesses in a county relative to January 4-31 2020. Daily values are reported as a seven-day moving average of the current day and the previous six days. Raw data on small business transactions and revenues come from Womply, a company that collects information from credit card processors. Womply provides a firm-based panel on total revenues of small businesses. As shown in Table 1, the average *Small business revenue* equals -20%, suggesting that small business revenue in an average county falls by 20% over February through June of 2020.

### *2.4 COVID-19 incidence*

The Economic Tracker also includes county-level data on COVID-19 cases. In particular, *Ln(Cases per capita)* equals the logarithm of one plus the number of confirmed cases per 100,000 people in a county on each day. The daily number of cases on a particular date is the cumulative number of cases since January 21, 2020. For a particular week, we use the value of *Ln(Cases per capita)* on Sunday of that week. As reported in Table 1, the average number of cumulative cases per 100,000 people in a county equals 154 across all counties and weeks. Figure 1 plots the cross-county distribution of the cumulative number of confirmed cases per 100,000 people as of the end of June 2020.

*2.5 Local bank structure and other country traits*

To assess whether small banks have a comparative advantage over big banks in funding local businesses during the pandemic, we construct two measures of the degree of small bank presence in a county. Using data from the Summary of Deposits (SoD) in 2019, *Share_small bank branches* equals the proportion of bank branches that belong to small U.S. banks. Following existing studies (e.g., Berger, Bouwman, and Kim 2017), we define a small bank as having total assets of $1 billion or less. The second measure, *Share_small bank deposits*, equals the proportion of deposits held by small U.S. banks in a county. Figure 2 plots the cross-county distribution of *Share_small bank branches*. As shown, there exists large variations across counties, including across counties within the same state. Table 1 shows that the average value of *Share_small bank branches* equals 0.4, with a standard deviation equal to 0.3. The other measure, *Share_small bank deposits*, exhibits a similar statistical pattern. Furthermore, we consider the overall availability of bank branches in a county. Specifically, *#Branches per capita* equals the total number of bank branches in a county divided by the population (in 100,000 people).

To isolate the relation between economic resilience to COVID-19 and local financial structure, we consider an array of other county characteristics that might influence local economic responses to COVID-19. First, to control for possibility that income shapes responses to the pandemic, as suggested by Chetty et al. (2020), we condition on *Income per capita*, which is from the Bureau of Economic Analysis and equals the total amount of personal income received by residents in a county divided by population in that county. Second, we use two measures of local demographics based on U.S. congressional data:[2] *%65+ pop* equals the proportion of local population aged above 65, and *Population density* equals the number of residents per square mile. We control for these demographics indicators because older

[2] https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america.

individuals and individuals in more dense locales are more susceptible to COVID-19. As a result, demographics may shape a community's economic resilience to the pandemic. Third, to capture a county's pre-pandemic economic conditions, we account for the unemployment rate in 2019 using data from the Bureau of Labor Statistics. *Unemployment rate* equals the proportion of unemployed labor force to total labor force in each county. In this regard, our analyses account for differences in local communities' sensitivity to COVID-19 arising from income, population age, population density, and initial economic conditions.[3]

*2.6 Graphical analyses*

To illustrate the connection between local economic resilience to the pandemic and the share of small banks in a county, we compare the evolution of employment in counties with "high" and "low" shares of small banks. We define a county as having a "high" share of small banks if *Share_small bank branches* is in the upper tercile of the cross-county sample. We categorize a county as having a "low" share of small banks if *Share_small bank branches* is in the lower tercile. We then plot the average value of *Employment* in each week from February through June for counties in the high- and low-small bank share counties respectively. As shown in Figure 3, employment falls by less in counties with a high share of small banks than it does in counties with a low share of small banks.

We next focus on the evolution of the structure of employment across low-, middle-, and high-income workers. We separately trace the deviation of the level of employment of low-, middle-, and high-workers relative to their pre-pandemic employment levels over the period from February through June 2020. As shown in Figure 4, the fall in employment is especially severe and enduring among low-income workers, as *Employment, low income workers* falls more sharply in March and April and recovers much more slowly after April than *Employment, middle income workers* and *Employment, high income workers*.

[3] For exposition purposes, we multiply the coefficient estimates on *Income per capita* and *Population density* by 1000 in the regression tables reported below.

We also find that the severity of the pandemic on low-income workers is less pronounced in counties with higher shares of small banks. Specifically, we focus on the evolution of *Employment, low income workers* across counties with different shares of small firms. We again differentiate between counties with a "high" share of small banks (*Share_small bank branches* in the upper tercile of counties) and counties with a "low" share of small banks (*Share_small bank branches* is in the lower tercile). We then plot the average value of *Employment, low income workers* for high- and low-small bank share counties respectively from February through June. As shown in Figure 5, the employment of low-income workers falls by less in counties with a high share of small banks than it does in counties with a low share of small banks.

These graphical analyses are consistent with the view that small banks enhance local economic resilience—especially among low-income workers. We next implement standard empirical methods that control for other local factors shaping economic responses to the pandemic to further assess the independent connection between local economic resilience to COVID-19 and the structure of local banking markets.

## 3. Empirical Strategy

To examine the heterogeneous effects of the COVID-19 pandemic on economic activities while differentiating by local banking structure, we employ the following regression model.

$$Y_{c,t} = \alpha_0 + \beta Ln(Cases\ per\ capita)_{c,t} * Share\ Small\ Bank_c + \gamma Ln(Cases\ per\ capita)_{c,t}$$
$$\boldsymbol{X_c} * Ln(Cases\ per\ capita)_{c,t} + \alpha_c + \alpha_{s,t} + \varepsilon_{c,t}, \quad (1)$$

where *c* and *t* index county and week, respectively. The dependent variable, $Y_{c,t}$, represents one of the indicators of local economic conditions in county *c* and week *t* (e.g., *Employment*). *Share Small Bank*$_c$ represents one of the two measures of the share of small banks in county *c* before the pandemic (i.e., *Share_small bank branches* or *Share_small bank deposits*). *Ln(Cases per capita)*$_{c,t}$ denotes the logarithm of one plus the cumulative number of confirmed cases per capita in county $c$ on Sunday of week $t$, which captures county-specific exposure to the pandemic. The coefficient of interest, $\beta$, captures how the relation between changes in county employment rates and COVID-19 infection rates differs by the share of small banks in counties. We estimate the model using OLS, with the standard errors clustered at the county level.

To isolate the effects of small banks on local economic resilience to COVID-19, we include an array of fixed effects and a set of interaction terms between $Ln(Cases\ per\ capita)_{c,t}$ and other county traits. Regarding fixed effects, we include county fixed effects, $\alpha_c$, that condition out all time-invariant factors at the county level, including differences in the level and structure of economic activities. The analyses also include state-week fixed effects, $\alpha_{s,t}$, to control for all time-varying factors at the state level, including differences in policy responses to the pandemic. By including state-time effects, we are essentially estimating the differential sensitivity of local economies to COVID-19 exposures between two counties within the same state and week. In addition, we condition on the interaction between $Ln(Cases\ per\ capita)_{c,t}$ and a vector of pre-pandemic country traits, $\boldsymbol{X_c}$ , that includes *#Branches per capita*, *Income per capita*, *%65+ pop*, *Population density*, and *Unemployment rate*.

## 4. Results

### *4.1 Small banks and employment during COVID-19, baseline results*

Results in Panel A of Table 2 show that as COVID-19 cases grew, employment fell, but it fell by less in counties with a larger proportion of small banks. Specifically, we first note in column 1 of Panel A that *Ln(Cases per capita)* enters negatively and significantly, suggesting that employment rates drop more in counties exposed to a larger number of COVID-19 cases. To interpret the economic magnitude, the coefficients from column 1 indicate that an average COVID-19 shock (*Ln(Cases per capita)* =2.8) is associated with a 2 percentage point (=2.8*0.72) drop of employment rates per week, which is equivalent to 19% of the standard deviation of *Employment*. Second, note in column 2 that the interaction term, *Share_small bank branches*Ln(Cases per capita)*, enters positively and significantly. This indicates that the adverse effect of COVID-19 on employment is milder in counties with a larger share of small banks in local banking markets. Furthermore, as shown in column 4, these results hold when measuring the share of small banks in a county using deposits rather than the number of branches.

These results hold when accounting for other county traits that might shape how employment in a county responds to local COVID-19 infection rates. Specifically, we include the interaction between *Ln(Cases per capita)* and each of the following county traits: *Income per capita*, *%65+ pop*, *Population density*, and *Unemployment rate*. As shown in columns 3 and 5, we continue to find that employment falls by less in response to COVID-19 in counties with a larger share of small banks. That is, the interaction term, *Share_small bank branches*Ln(Cases per capita)* in column 3 and *Share_small bank deposits*Ln(Cases per capita)* in column 5, continues to enter positively and significantly, suggesting that the proportion of small banks in local banking markets exerts an independent effect on employment resilience to COVID-19.

To illustrate the degree to which small banks in a county mitigate the adverse effects of local COVID-19 cases on local employment, consider the coefficient estimates from column 3 of Panel A. Furthermore, consider an average weekly COVID-19 shock of 2.8, which is the sample mean of *Ln(Cases per capita)*. Next compare two otherwise similar counties, except that the "high" small bank share county has one standard deviation larger small bank share than the "low" small bank share county, so that the difference in *Share_small bank branches* between the two counties is 0.33. The coefficient estimates from column 3 indicate that the negative impact of an average weekly COVID-19 shock on the weekly decline in employment would be 0.68 (=0.733*0.33*2.8) percentage points smaller in the county with a "high" share of small banks than in the county with a "low" share of small banks. This is equivalent to 6% of the standard deviation of *Employment* (=10.5).

When examining unemployment insurance claims in Panel B of Table 2, we find that claims increase with COVID-19 infection rates, but they rise by less in counties with a larger share of small banks. As shown in column 1, the linear term *Ln(cases per capita)* enters positively and significantly, indicating that the rate of unemployment insurance claim is higher in counties with higher COVID-19 infection rates. The interaction between *Ln(cases per capita)* and the proportion of small banks in a county, i.e., *Share_small bank branches* or *Share_small bank deposits*, enters negatively and significantly in all columns, suggesting that unemployment insurance claim rates increase by less in response to COVID-19 in counties with a greater share of small banks. Again, the effects of small banks on unemployment insurance claims hold when including (a) a full set of county and state-week fixed effects, and (b) the interaction between *Ln(cases per capita)* and each county's total number of bank branches per capita in the county, income per capita, percentage of people over the age of 65, population density, and pre-pandemic unemployment rate. Taken together, the baseline results reported in Table 2 are consistent with the view that small banks have a comparative advantage in cushioning the adverse effects of the duress triggered by COVID-19 on labor markets.

*4.2 Income distributional implications of small banks*

We next examine the income distributional implications of small banks by separately examining the cushioning effects of small banks in response to COVID-19 infection rates on the employment rates of low-, middle-, and high-income workers. More specifically, we re-estimate equation (1) in which the dependent variable is either (1) *Employment, low income workers*, which equals the percentage change in the employment rate low-income workers relative to January 2020, where low-income workers are defined as those in the bottom quartile of the income distribution, (2) *Employment, middle income workers*, which equals the percentage change in the employment rate of middle-income workers relative to January 2020, where middle-income workers are defined as those in the middle two quartiles of the income distribution, and (3) *Employment, high income workers*, which equals the percentage change in the employment rate of high-income workers relative to January 2020, where high-income workers are defined as those in the top quartile of the income distribution. Each of these employment rate measures is computed at the county-week level and is measured at the percentage change from the county's employment level in January of 2020.

Results reported in Table 3 suggest that small banks have a particularly strong cushioning effect on the employment of low-income workers during the pandemic. The dependent variable in columns 1 – 4 is *Employment, low-income workers*. As shown in columns 1 – 4, where the dependent variable is *Employment, low-income workers*, the coefficient estimates on *Share_small bank branches*Ln(cases per capita)* and *Share_small bank deposits*Ln(cases per capita)* are positive and statistically significant. These findings suggest that the employment of low-income workers falls by less in response to local COVID-19 infections in counties with a higher proportion of small banks. With respect to the size of the estimated effect, consider again an average weekly COVID-19 shock (=2.8), and compare two otherwise similar counties, except that the "high" small bank share county has one standard deviation (=0.33) larger small bank share than the "low" small bank share county. The coefficient estimates from column 2 indicate that the negative impact of an average weekly COVID-19 shocks on the weekly decline in employment of low income workers would be 1.3 (=1.427*0.33*2.8) percentage points smaller in the "high" small bank share county than in the "low" small bank share county. This is equivalent to 8% of the standard deviation of *Employment, low-income workers*. In contrast, when examining employment rates of middle-income and high-income workers, the coefficient estimates on these interaction terms are economically small and not statistically robust (columns 5 – 12). The Table 3 results indicate that the share of small banks in a county mitigated the adverse impact of local COVID-19 infection rates on the local employment of low-income workers.

There might be concerns that the connection between the share of small banks in a county and the reaction of local employment to COVID-19 infection rates is driven by bank traits other than the local presence of small banks. To mitigate the concern, we control for an additional set of county traits, including banking market concentration (HHI) and county-aggregated bank characteristics (including *Liquid assets*, *Equity ratio*, *Tier 1 ratio*, NPL, and ROA averaged at the county level). *Banking market concentration* equals the HHI of each bank's market share in a county as of 2019. Regarding county-aggregate bank characteristics, take *Liquid assets* as an illustrative example, we calculate the county-specific *Liquid assets* as the weighted average of bank-specific *Liquid assets* across banks in each county, weighted each bank by its share of deposits in that particular county. Using the same approach, we construct county-specific bank characteristics for each of the bank traits.

As shown in Table 4, conditioning on these additional bank market traits and the interaction with *Ln(cases per capita)* does not alter the results on the connection between the proportion of small banks and the reaction of employment to local COVID-19 infection rates across income distribution. The interaction terms between *Ln(cases per capita)* and the proportion of small banks in a county, i.e., *Share_small bank branches* or *Share_small bank deposits*, continue to enter positively and significantly in employment for low-income workers. In addition, the estimated coefficients on the interaction terms are similar to those in Table 3.

*4.3 Small banks and small business revenue during COVID-19*

One implication of the view that small banks have a comparative advantage in lending to local businesses during the economic turmoil triggered by local COVID-19 infection rates is that local firms in counties with a higher proportion of small banks will be better able to maintain their operations. To assess this implication, we examine whether the revenues of small local firms fall by less in response to COVID-19 in counties in which small banks compose a greater share of the local banking market. We employ the same empirical model as in the employment analyses, but the dependent variable now becomes *Small business revenue*, which equals the percent change in seasonally adjusted net revenues for small businesses in each county relative to its pre-pandemic level.

Results reported in Table 5 show that in response to a county's COVID-19 infections, small business revenue drops by less in counties with higher share of small bank. Column 1 shows that the county-specific COVID-19 infection rate, *Ln(cases per capita)*, enters negatively.

Note, however, that the interaction between *Ln(cases per capita)* and the measure of the share of small banks in the local banking market (*Share_small bank branches* or *Share_small bank deposits*) enters positively and significantly in columns 2 – 5. This suggests that *Small business revenue* falls by less in response to the pandemic in counties with a higher share of small banks. These findings are consistent with the view that small banks have a comparative advantage in financing small firms during the pandemic and this funding allows those small businesses to operate more effectively and generate greater revenues.

**5. Instrumental Variables and the Small Bank-Small Firm Mechanism**

In assessing the degree to which the share of small banks in a county shapes its resilience to local COVID-19 infection rates, we have conditioned on the potential influences of many other local characteristics. Besides controlling for county and state-week fixed effects, the analyses have conditioned on the interaction between county infection rates and county-level information on (a) income per capita, (b) the proportion of the population above 65 years old, (c) population density, (d) the pre-pandemic unemployment rates, and (e) the number of bank branches per capita. Thus, we have so far used a control function approach to address omitted variable concerns and draw inferences about how small banks shape a local economy's resilience to the COVID-19 infections during the first half of 2020.

Despite the extensive controls included in the analyses above, there could be omitted county-specific features that are highly correlated with the local share of small banks and it might be these omitted features, and not financial structure, that shape cross-county responses to the pandemic. To further address this concern, we use two strategies. First, we use an instrumental variable to identify the impact of the share of small banks on cross-county responses to local COVID-19 infection rates. Second, we examine the direct link between small banks and their lending to small firms in response to the pandemic. Third, we investigate whether the impact of small banks manifests primarily among small firms. Since the theoretical mechanism linking small banks to economic resilience operates through small banks having a comparative advantage over larger banks in lending to small firms during periods of economic turmoil, evidence of this link enhances identification and hence the interpretation of the results.

*5.1 IV tests*

We use an instrumental variable (IV) for cross-county differences in the share of small banks. In particular, we use a measure of the consolidation of the local banking market triggered by the merger of out-of-state banks. For each county, we compute *#Mergers by out-of-state banks* as the number of mergers by two out-of-state banks during the ten years, 2010 – 2019, before the COVID-19 pandemic, where both acquiring and target banks have at least one branch located in the county prior to the merger. Thus, for a county *c* located in state *s*, the merger involves two banks that are not headquartered in state *s*, where each bank has at least one branch in county *c*. This merger-induced consolidation will tend to give the larger bank a competitive advantage in county *c*, reducing the role of small banks in the county. Consistent with this view, we find that a county's exposure to *#Mergers by out-of-state banks* over the past decade is negatively associated with the market share of small banks at the end of 2019. The identifying assumption is that the decision of two banks headquartered in states different from county *c* to merge during the 2010-2019 period does not reflect local conditions in county *c* that drive the county's resilience to the 2020 pandemic.

We then reassess the degree to which the share of small banks in a county shapes its resilience to local COVID-19 infection rates using two-stage least squares. In particular, as the excluded the instrument for *Share_small bank branches*Ln(cases per capita)*, we use *#Mergers by out-of-state banks*Ln(cases per capita)*. In the second stage, we use the predicted values of *Share_small bank branches*Ln(cases per capita)* to reevaluate the baseline regression specifications using this IV approach.

The first-stage estimation results show that the instruments are strongly correlated with *Share_small bank branches*Ln(cases per capita)*. As shown in column 2 of Table 6, the Fstatistic of the null hypothesis that the excluded instruments do not account for cross-county variations in the share of small banks prior to the pandemic equals 51, suggesting that the instruments are not weak. With respect to the exclusion restriction, we note that the instruments are constructed from a plausibly exogenous source of variation: out-of-state bank mergers.

As shown in Table 6, the second stage of the IV analyses confirms the results reported above: a larger share of small banks in a county mitigates the adverse shock of COVID-19 on employment, especially the employment of low-income workers. As reported in column 1 of Table 6, the instrumented *Share_small bank branches*Ln(cases per capita)* enters the second-stage regressions positively and significantly. The results hold when controlling for county and state-week fixed effects. The estimated "cushioning" effect of small banks on employment during the pandemic is economically large. To illustrate the economic magnitude, consider an average weekly COVID-19 shock (*Ln(Cases per capita)* =2.8), and two otherwise similar counties, except that the share of small banks in a county ("high" small bank share county) is one standard deviation (0.33) larger than that of the other county ("low" small bank share county). The coefficient estimates in column 1 indicate that employment rates in the "high" small bank share county would fall by 1.8 (=1.92*0.33*2.8) percentage points less than that of the "low" small bank share county. This is large, as it corresponds to 17% of the standard deviation of *Employment*. Furthermore, as shown in column (3), the resilience-enhancing effects of small banks are especially pronounced for low-income workers.

The IV analyses also confirm that in response to COVID-19 infections, small business revenues drop by less in counties with higher small bank shares. As stressed above, the argument that small banks have a comparative advantage in funding small firms implies that small firms in counties with a higher proportion of small banks will perform better during the pandemic than otherwise similar firms in counties with a lower proportion of small banks. One implication of the view that small banks have a comparative advantage in lending to local businesses during the economic turmoil triggered by local COVID-19 infection rates is that local firms in counties with a higher proportion of small banks will be better able to maintain their operations. As shown in column 9 of Table 6, the IV regression results are consistent with the view that small local banks help cushion the adverse effects of the pandemic on small businesses to a greater degree than larger banks, bolstering small firm operations and revenues.

*5.2 Bank lending to small business during COVID-19, small vs. large banks*

The analyses so far indicate that employment—especially employment of low-income workers—and small-firm revenues are more resilient to the COVID-19 pandemic in counties with a higher proportion of small banks. One explanation for these results is that small banks have a comparative advantage in lending to small firms during period of economic turmoil, cushioning the impact of the pandemic in counties with larger small bank shares. The findings on low-income workers are consistent with this explanation since small firms disproportionately employ low-income workers. Similarly, the findings on small business revenues support this explanation as they suggest that high small-bank counties support small firms, allowing them to better maintain operations and revenues. We now examine a specific theoretical mechanism of how small banks boost economic resilience: the direct link between small banks and their lending to small firms during the pandemic.

To examine lending by small banks to small firms, we move from the county-week analyses of economic resilience to a cross-sectional analysis of the relation between changes in a bank's lending to small firms and the bank's exposure to business clients affected by local COVID-19 cases. Since we do not have data on the addresses of each client, we measure the exposure of a bank's business clients to COVID-19 by building on the findings in Nguyen (2019), who shows that banks tend to make loans to businesses that are geographically very close to their branches. Thus, we compute *Bank exposure* as the weighted average of *ln(cases per capita)* across counties in which the bank has branches, where the weights are the shares of deposits held by the bank's branches in those counties. To match *Bank exposure* to the quarterly Call Reports data, we compute *Bank Exposure* using *Ln(cases per capita)* as of June 30, 2020.

To measure each bank's lending to small firms, we follow the classification of Community Reinvestment Act (CRA) and define small business loans as loans with origination values of $1 million. We measure changes in a bank's lending to small firms, *Small business loan growth,* as the growth in the dollar amount of loans to small businessesMore specifically, *Small business loan growth* equals the log difference between small business loans (in the dollar amount) between Q2-2020 and Q4-2019 for each bank. We also consider overall C&I loan growth and PPP loans. *C&I loan growth* equals the log difference between commercial & industrial loans between Q2-2020 and Q4-2019 for each bank. *PPP loans* equals the amount of PPP loans outstanding as of Q2-2020 scaled by total assets as of Q4-2019. According to Li and Strahan (2021), bank credit supply through the CARES Act's Paycheck Protection Program (PPP) accounts for a major of bank loans during first few months of 2020.

We consider two measures of bank size in our analyses of the connection between bank size and lending to small firms. First, as a continuous measure of bank size, we use *Ln(Assets)*, which equals the natural log of total assets of each bank at the close of 2019. Second, as a discrete measure, we use *Small bank*, which equals one if a bank's total assets at the close of are below $1 billion and zero otherwise.

Given these measures, we estimate the following regression model:

$$Small\ business\ loan\ growth_b = \alpha_0 + \beta Bank\ exposure_b * Size_b + \gamma Bank\ exposure_b + X_b + \alpha_s + \varepsilon_b, \quad (2)$$

where there is one observation per bank, *b*, and where $Size_b$ is either *Ln(Assets)* or *Small bank.* The regression also conditions on, $X_b$, which is a vector of bank characteristics including *Ln(Assets)* (the log of book value of total assets), the *Equity ratio* (the ratio of total equity to total assets), *ROA* (net income divided by total assets), *Single market* (an indicator of whether a bank operates in only one market or not), Tier 1 capital (the ratio of tier 1 capital to risk-weighted assets), Liquid assets (the ratio of liquid assets to total assets), and NPL (non-performing loans to total assets). The term, $\alpha_s$, denotes a set of state fixed effects for each bank's headquarters. We estimate equation (2) using OLS, and report heteroskedasticity robust standard errors.

As reported in Table 7, there is a larger increase in small business lending by small banks in response to COVID-19 than by large banks. First note that there is a strong, positive relation between *Bank exposure* and Small business loan growth, measured either as *Small business loan growth* as shown in column 1. This finding suggests that banks increase lending to small firms during the first few months of the pandemic. Second, note that when distinguishing banks by size, we find that the increase in small business lending during COVID-19 is stronger among smaller banks. As shown in columns 2 and 3, *Ln(Assets)*Bank exposure* enters negatively and significantly, and *Small bank*Bank exposure* enters positively and significantly, suggesting that smaller banks boost lending to small firms more in reaction to the pandemic than larger banks. When using the discrete measure of bank size (i.e., *Small bank*), we find that the linear term, *Bank exposure*, enters insignificantly in column 3. These findings indicate that small banks with total assets up to $1 billion increased lending to small firms, whereas large banks with more than $1 billion total assets did not significantly change lending to small firms. The results hold when examining *C&I loan growth* as reported in columns 4 – 6. Furthermore, columns 7 – 9 show that small banks provide more *PPP loans* in response to the Covid-19 exposure. This is consistent with the findings in Li and Strahan (2021), which stresses a new benefit of bank relationships: small banks prioritize serving their relationship borrowers, facilitating small firms to access government-subsidized lending. Overall, these cross-bank analyses are consistent with the view that small banks have a comparative advantage in providing liquidity to small firms during periods of economic duress.

### *5.3 Employment resilience to COVID-19, small vs. large firms*

We next evaluate whether employment at small firms falls less in areas with a larger share of small banks. To do this, we use the LEHD Quarterly Workforce Indicators (QWI) database, which provides disaggregate employment data at the county, two-digit NAICS sector, and firm size groups. The frequency of the QWI data is at the quarterly level. We estimate the following model specification.

$$\begin{aligned} Emp_{c,j,type,t} = {} & \beta Share\ Small\ Bank_c * Ln(Cases\ per\ capita)_{c,t} * \boldsymbol{type} \\ & + \gamma Ln(Cases\ per\ capita)_{c,t} + \rho Ln(Cases\ per\ capita)_{c,t} * \boldsymbol{type} \\ & + \theta Share\ Small\ Bank_c * Ln(Cases\ per\ capita)_{c,t} + \boldsymbol{X_c} \\ & * Ln(Cases\ per\ capita)_{c,t} + \alpha_{c,j,type} + \alpha_{j,t} + \alpha_{type,t} + \alpha_{s,t} + \varepsilon_{c,j,type,t} \end{aligned}$$

Where c, j, type, and t index county, sector, firm size groups, and quarter, respectively. We consider three firm size groups based 1–49, 50–499, and 500+ employees.

The estimation results reported in Table 8 are consistent with our hypothesis. As shown, the effects of the share of small bank on employment are more pronounced among small firms. This is consistent with the notion that that small banks provide liquidity to small firms during periods of economic duress, mitigating the adverse effects of the Covid-19 pandemic on employment.

## 6. Conclusions

In this paper, we examine how the proportion of small banks operating in a local economy influences the resilience of that economy with respect to employment, the distribution of employment across low-, middle-, and high-income workers, the revenues of small local firms, and the countercyclical funding of small businesses to the COVID-19 pandemic. We exploit high-frequency, county-level data on employment, small business revenue, and COVID-19 cases.

We discover that employment, especially the employment of low-income workers, falls by less in response to local COVID-19 infection rates in counties with a larger proportion of small banks. Furthermore, the pandemic-induced drop in small business revenue was milder among counties in which small banks compose a larger share of local banking markets. Finally, we find that in response to the pandemic, small banks increase their small business lending more than larger banks. The evidence suggests that small banks have a comparative advantage in ameliorating information asymmetries and financing small firms following the adverse shock of COVID-19.

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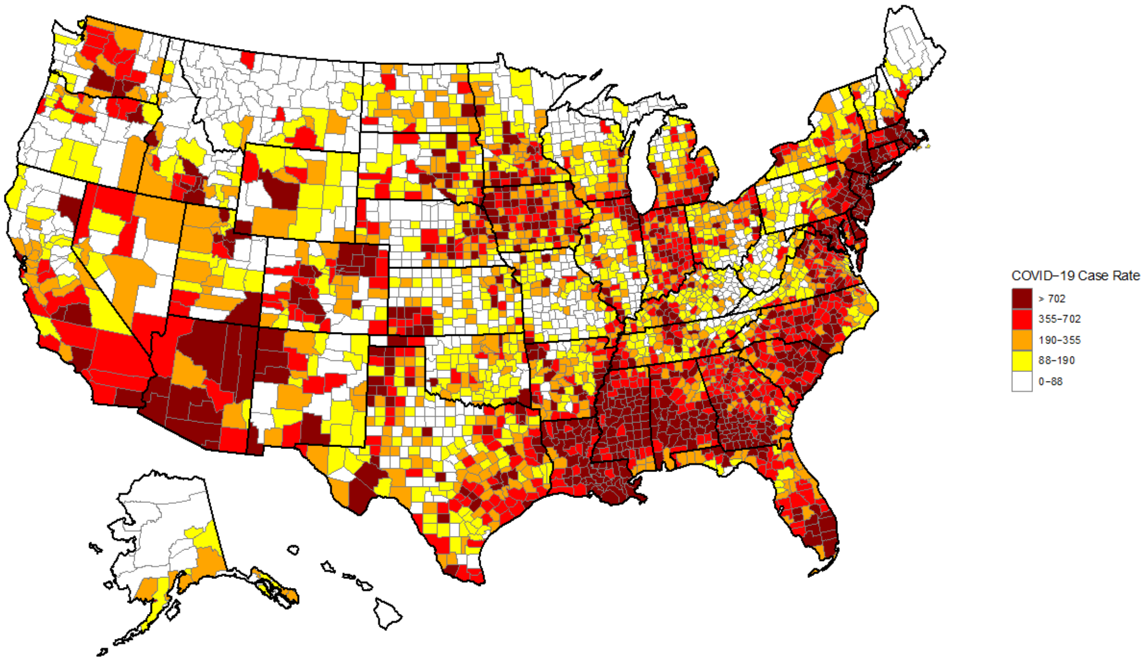


**Figure 1. # COVID-19 cases by county, as of June 2020**
This figure plots the cumulative number of confirmed COVID-19 cases per 100,000 population for all U.S. counties as of June 30, 2020. Darker colors indicate a larger number of confirmed cases per capita.

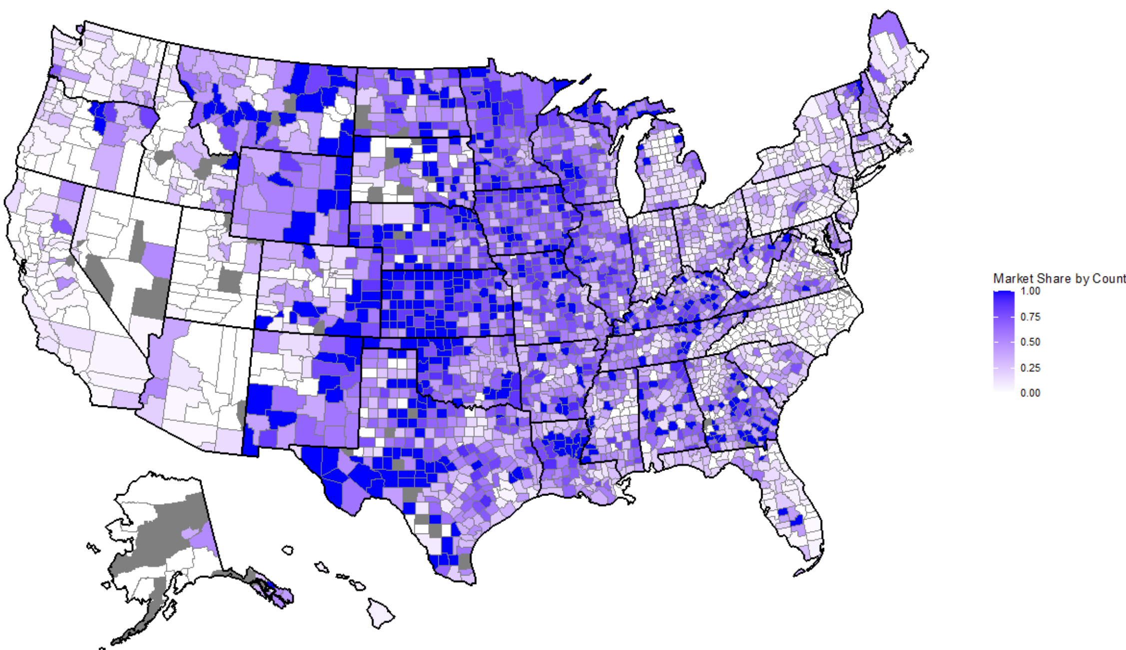


**Figure 2. Share of small bank branches by county**
This figure plots the proportion of small bank branches for all U.S. counties as of June 30, 2019. Darker colors indicate a larger share of small bank branches.

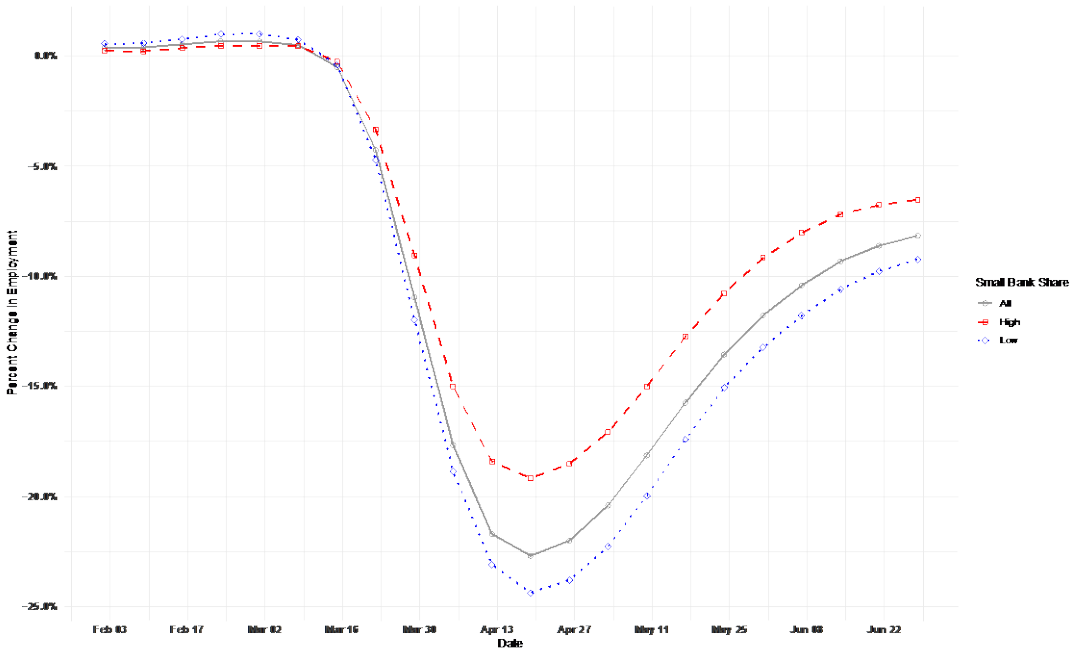


**Figure 3. Employment in counties with high vs. low small bank share**

This figure plots the employment rates over time while dividing counties into groups with high- or low-groups of small bank shares. High (low) small bank share counties refer to those with the proportion of small bank branches is above (below) the top (bottom) tercile of the sample value of *Share_small bank branches*.

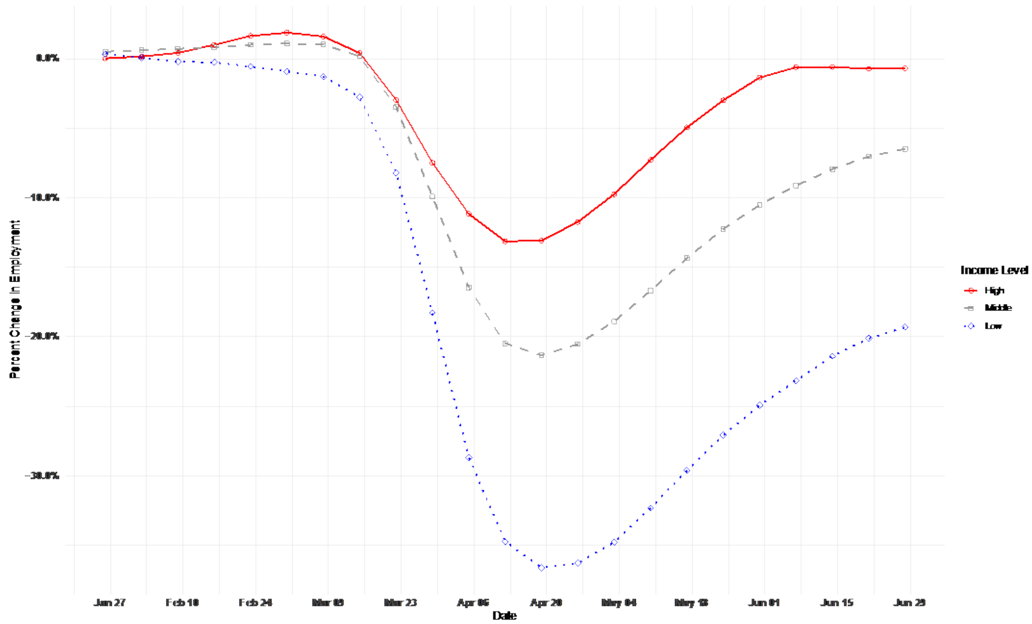


**Figure 4. Employment of low-, middle-, and high-income workers**

This figure plots the trends of employment rates of low-, middle-, and high-income workers over time. Low-income workers are those in the bottom quartile of the income distribution, middle-income workers are those in the middle two quartiles of the income distribution, and high-income workers are those in the top quartile of the income distribution.

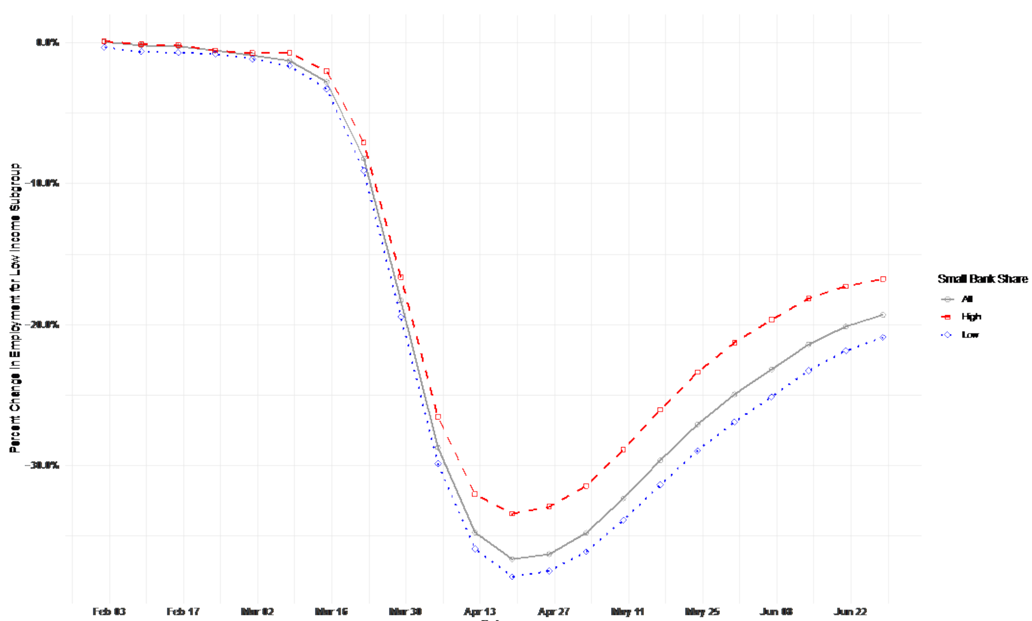


**Figure 5. Employment of low-income workers, in counties with high vs. low small bank share**

This figure plots the employment rates of low-income workers over time while dividing counties into groups with high- or low-groups of small bank shares. High (low) small bank share counties refer to those with the proportion of small bank branches is above (below) the top (bottom) tercile of the sample value of *Share_small bank branches*.

**Table 1 Summary Statistics**

| variable | N | mean | sd | min | p10 | p25 | p50 | p75 | p90 | max |
|---|---|---|---|---|---|---|---|---|---|---|
| ln(cases per capita) | 33930 | 2.83 | 2.51 | 0 | 0 | 0 | 3.24 | 4.99 | 6.08 | 9.08 |
| cases per capita | 33930 | 164 | 409 | 0 | 0 | 0 | 24.5 | 146 | 436 | 8744 |
| Employment | 17580 | -9.611 | 10.5 | -35.6 | -25.1 | -17.1 | -7.59 | -0.231 | 1.67 | 8.2 |
| Unemployment Insurance Claims | 23454 | 1.163 | 1.625 | 0 | 0.084 | 0.192 | 0.619 | 1.56 | 2.95 | 45.5 |
| Employment, low income workers | 10914 | -18.26 | 15.92 | -52.2 | -40.5 | -30.9 | -17.7 | -2.46 | 0.818 | 5.56 |
| Employment, middle income workers | 12784 | -8.603 | 10.19 | -34 | -23.8 | -15.6 | -6.41 | 0.174 | 2.18 | 10.3 |
| Employment, high income workers | 7552 | -3.651 | 6.776 | -22.7 | -13.7 | -7.74 | -1.74 | 1.16 | 3.19 | 10.7 |
| Small business revenue | 9856 | -20.78 | 21.47 | -85.1 | -49.6 | -37.5 | -20.1 | -3.54 | 5.92 | 41.1 |
| share_small bank branches | 1797 | 0.4 | 0.325 | 0 | 0 | 0.1 | 0.333 | 0.667 | 0.9 | 1 |
| share_small bank deposits | 1797 | 0.376 | 0.344 | 0 | 0 | 0.052 | 0.267 | 0.671 | 0.936 | 1 |
| #branches per capita | 1801 | 37.6 | 27.7 | 0 | 15.5 | 21.3 | 29.5 | 44.4 | 67.8 | 255 |
| Income per capita | 1814 | 45735 | 13755 | 19141 | 33736 | 38013 | 43296 | 50107 | 58878 | 251728 |
| %65+ pop | 1814 | 16.9 | 4.29 | 6.16 | 11.9 | 14.2 | 16.5 | 19 | 22 | 57.3 |
| Population density | 1814 | 381 | 2303 | 0.298 | 10.5 | 27.6 | 69.6 | 210 | 595 | 71616 |
| Unemployment rate | 1814 | 3.86 | 1.29 | 1.6 | 2.6 | 3 | 3.6 | 4.5 | 5.4 | 18.3 |

## Table 2 local financial structure and economic resilience to Covid

The table reports regression results of how employment rates (Panel A) and unemployment insurance claims (Panel B) respond to COVID-19 as functions of pre-pandemic share of small banks in local banking markets. The dependent variable is the employment level relative to January 2020 of each county in a week (Panel A) and the number of initial claims per 100 people in the 2019 labor force (Panel B). *COVID19* is the number of confirmed COVID-19 cases per 100,000 people in a county by the end of each week. To measure the proportion of small banks in a county, we use *Share_small bank branches* or *Share_small bank deposits*. The analyses cover the period from February 2020 through June 2020. We include county and state by week fixed effects. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

**Panel A: Employment**

| | Employment | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ln(cases per capita) | -0.721*** | -0.730*** | -0.871** | -0.717*** | -0.879** |
| | (0.184) | (0.234) | (0.407) | (0.235) | (0.408) |
| share_small bank branches*ln(cases per capita) | | 1.095*** | 0.733** | | |
| | | (0.260) | (0.292) | | |
| share_small bank deposits*ln(cases per capita) | | | | 1.057*** | 0.729*** |
| | | | | (0.235) | (0.262) |
| #branches per capita*ln(cases per capita) | | -0.008 | -0.006 | -0.007 | -0.006 |
| | | (0.007) | (0.007) | (0.007) | (0.007) |
| Income per capita*ln(cases per capita) | | | -0.006* | | -0.006* |
| | | | (0.003) | | (0.003) |
| %65+ pop*ln(cases per capita) | | | 0.033** | | 0.033** |
| | | | (0.014) | | (0.014) |
| population density*ln(cases per capita) | | | -0.008 | | -0.008 |
| | | | (0.008) | | (0.008) |
| Unemployment rate*ln(cases per capita) | | | 0.026 | | 0.029 |
| | | | (0.053) | | (0.052) |
| County FE | Y | Y | Y | Y | Y |
| State-time FE | Y | Y | Y | Y | Y |
| Observations | 17,558 | 17,536 | 17,536 | 17,536 | 17,536 |
| Adjusted R-squared | 0.864 | 0.866 | 0.867 | 0.866 | 0.867 |
| # of clusters | 799 | 798 | 798 | 798 | 798 |

**Panel B: Unemployment Insurance Claims**

| | Unemployment Insurance Claims | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ln(cases per capita) | 0.059*** | 0.079*** | 0.099** | 0.073*** | 0.091** |
| | (0.014) | (0.017) | (0.039) | (0.017) | (0.038) |
| share_small bank branches*ln(cases per capita) | | -0.068*** | -0.076*** | | |
| | | (0.022) | (0.023) | | |
| share_small bank deposits*ln(cases per capita) | | | | -0.047** | -0.053*** |
| | | | | (0.019) | (0.020) |
| #branches per capita*ln(cases per capita) | | 0.0002 | 0.001** | 0.0002 | 0.0005* |
| | | (0.000) | (0.000) | (0.000) | (0.000) |
| Income per capita*ln(cases per capita) | | | -0.001** | | -0.001** |
| | | | (0.000) | | (0.000) |
| %65+ pop*ln(cases per capita) | | | -0.002 | | -0.002 |
| | | | (0.001) | | (0.001) |
| population density*ln(cases per capita) | | | 0.003*** | | 0.003*** |
| | | | (0.001) | | (0.001) |
| unemployment rate*ln(cases per capita) | | | 0.009* | | 0.009* |
| | | | (0.005) | | (0.005) |
| County FE | Y | Y | Y | Y | Y |
| State-time FE | Y | Y | Y | Y | Y |
| Observations | 23,435 | 23,172 | 23,172 | 23,172 | 23,172 |
| Adjusted R-squared | 0.749 | 0.751 | 0.751 | 0.751 | 0.751 |
| # of clusters | 1422 | 1405 | 1405 | 1405 | 1405 |

## Table 3 local financial structure and economic resilience to Covid, employment by income level

The table reports regression results of how employment rates respond to COVID-19 as functions of pre-pandemic share of small banks in local banking markets, while examining employment rates across different income groups. *Employment, low income workers* represents the employment level for workers in the bottom quartile of the income distribution (incomes approximately under $27,000). *Employment, middle income workers* represents the employment level for workers in the middle two quartiles of the income distribution (incomes approximately $27,000 to $60,000). *Employment, high income workers* represents the employment level for workers in the top quartile of the income distribution (incomes approximately over $60,000). Other variables are the same as before. *County traits* include *Income per capita*, *%65+ pop*, *Population density*, and *Unemployment rate*. We include county and state by week fixed effects. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

| | Employment, low income workers | | | | Employment, middle income workers | | | | Employment, high income workers | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| ln(cases per capita) | -1.354*** | -2.402*** | -1.419*** | -2.429*** | -0.788*** | -0.383 | -0.762*** | -0.388 | -0.438 | -0.067 | -0.436 | -0.064 |
| | (0.403) | (0.608) | (0.409) | (0.609) | (0.252) | (0.504) | (0.250) | (0.504) | (0.285) | (0.488) | (0.284) | (0.489) |
| share_small bank branches* ln(cases per capita) | 2.022*** | 1.427** | | | 0.816** | 0.029 | | | 0.403 | -0.269 | | |
| | (0.630) | (0.693) | | | (0.375) | (0.404) | | | (0.453) | (0.523) | | |
| share_small bank deposits* ln(cases per capita) | | | 1.924*** | 1.329** | | | 1.022*** | 0.289 | | | 0.584 | -0.111 |
| | | | (0.598) | (0.662) | | | (0.394) | (0.421) | | | (0.440) | (0.500) |
| #branches per capita* ln(cases per capita) | 0.010 | 0.019 | 0.014 | 0.023* | -0.005 | 0.001 | -0.006 | -0.001 | -0.019* | -0.014 | -0.019* | -0.016 |
| | (0.012) | (0.015) | (0.012) | (0.014) | (0.008) | (0.008) | (0.007) | (0.008) | (0.010) | (0.012) | (0.010) | (0.011) |
| County FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| State-time FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| County traits*ln(cases per capita) | N | Y | N | Y | N | Y | N | Y | N | Y | N | Y |
| Observations | 10,826 | 10,826 | 10,826 | 10,826 | 12,674 | 12,674 | 12,674 | 12,674 | 7,442 | 7,442 | 7,442 | 7,442 |
| Adjusted R-squared | 0.905 | 0.906 | 0.904 | 0.906 | 0.877 | 0.882 | 0.877 | 0.882 | 0.854 | 0.862 | 0.854 | 0.862 |
| # of clusters | 493 | 493 | 493 | 493 | 577 | 577 | 577 | 577 | 339 | 339 | 339 | 339 |

## Table 4 Robustness tests

The table reports regression results of how employment rates respond to COVID-19 as functions of pre-pandemic share of small banks in local banking markets, while controlling for additional country traits. Additional county traits include bank concentration (HHI) and county-aggregated bank characteristics (liquid assets, equity ratio, tier 1 ratio, non-performing loans, and ROA). *County traits* include *Income per capita*, *%65+ pop*, *Population density*, and *Unemployment rate*. Other variables are defined the same as before. We include county and state by week fixed effects. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

| | Employment, low income workers | | Employment, middle income workers | | Employment, high income workers | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ln(cases per capita) | -3.290*** | -3.406*** | -2.062*** | -2.076*** | -0.100 | -0.080 |
| | (1.073) | (1.070) | (0.797) | (0.797) | (0.794) | (0.795) |
| share_small bank branches*ln(cases per capita) | 1.620** | | -0.141 | | -0.528 | |
| | (0.709) | | (0.408) | | (0.546) | |
| share_small bank deposits*ln(cases per capita) | | 1.599** | | 0.202 | | -0.461 |
| | | (0.688) | | (0.429) | | (0.541) |
| County traits*ln(cases per capita) | Y | Y | Y | Y | Y | Y |
| Additional County traits*ln(cases per capita) | Y | Y | Y | Y | Y | Y |
| County FE | Y | Y | Y | Y | Y | Y |
| State-time FE | Y | Y | Y | Y | Y | Y |
| Observations | 10,826 | 10,826 | 12,674 | 12,674 | 7,442 | 7,442 |
| Adjusted R-squared | 0.907 | 0.907 | 0.883 | 0.883 | 0.862 | 0.862 |
| # of clusters | 493 | 493 | 577 | 577 | 339 | 339 |

**Table 5 local financial structure and small business revenue during Covid-19**

The table reports regression results of how small business revenues respond to COVID-19 as functions of pre-pandemic share of small banks in local banking markets. *Small business revenue* is the percent change in seasonally-adjusted net revenue for small businesses relative to January 4-31 2020. Other variables are the same as before. *County traits* include *Income per capita*, *%65+ pop*, *Population density*, and *Unemployment rate*. We include county and state by week fixed effects. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

| | Small business revenue | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ln(cases per capita) | -2.150*** | -1.775*** | -1.277* | -1.660*** | -1.271* |
| | (0.493) | (0.564) | (0.768) | (0.569) | (0.765) |
| share_small bank branches*ln(cases per capita) | | 4.267*** | 1.990** | | |
| | | (0.772) | (0.814) | | |
| share_small bank deposits*ln(cases per capita) | | | | 4.091*** | 1.845** |
| | | | | (0.874) | (0.861) |
| #branches per capita*ln(cases per capita) | | -0.038** | 0.003 | -0.034** | 0.006 |
| | | (0.016) | (0.018) | (0.016) | (0.018) |
| County FE | Y | Y | Y | Y | Y |
| State-time FE | Y | Y | Y | Y | Y |
| County traits*ln(cases per capita) | - | N | Y | N | Y |
| Observations | 9,724 | 9,724 | 9,724 | 9,724 | 9,724 |
| Adjusted R-squared | 0.847 | 0.851 | 0.856 | 0.850 | 0.855 |
| # of clusters | 443 | 443 | 443 | 443 | 443 |

**Table 6 local financial structure and economic resilience to Covid-19, IV**

This table reports the 2SLS regression results of how employment rates and small business revenues respond to COVID-19 as functions of pre-pandemic share of small banks in local banking markets. Columns with the odd number report the second-stage estimation results. The dependent variables in column 1, 3, 5, 7, and 9 are *Employment*, *Employment, low-income workers*, *Employment, middle-income workers*, *Employment, high-income workers*, and *Small business revenue*, respectively. Columns with the even number report the first-stage result, so the dependent variable is the endogenous variable, *Share_small bank branches*Ln(cases per capita)*. The excluded instrument is *#Mergers by out-of-state banks*Ln(cases per capita)*. We include county and state by week fixed effects. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

| | Employment | First-stage | Employment, low income workers | First-stage | Employment, middle income workers | First-stage | Employment, high income workers | First-stage | Small business revenue | First-stage |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| ln(cases per capita) | -0.726*** | 0.024 | -1.047** | -0.099*** | -0.652** | -0.019 | -0.399 | -0.038 | -1.659*** | -0.019 |
| | (0.235) | (0.029) | (0.461) | (0.027) | (0.285) | (0.033) | (0.287) | (0.028) | (0.576) | (0.032) |
| share_small bank branches* ln(cases per capita) | 1.926* | | 4.308** | | 4.031** | | 1.074 | | 7.181** | |
| | (1.008) | | (1.852) | | (1.818) | | (2.884) | | (3.201) | |
| #branches per capita* ln(cases per capita) | -0.014 | 0.007*** | -0.010 | 0.009*** | -0.027* | 0.007*** | -0.022 | 0.005*** | -0.056** | 0.006*** |
| | (0.009) | (0.001) | (0.019) | (0.001) | (0.014) | (0.001) | (0.014) | (0.001) | (0.024) | (0.001) |
| #Mergers by out-of-state banks*ln(cases per capita) | | -0.077*** | | -0.061*** | | -0.057*** | | -0.036*** | | -0.051*** |
| | | (0.011) | | (0.010) | | (0.010) | | (0.010) | | (0.010) |
| County FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| State-time FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 17,536 | 17,536 | 10,826 | 10,826 | 12,674 | 12,674 | 7,442 | 7,442 | 9,724 | 9,724 |
| Weak_ID_FTest | | 51.52 | | 40.45 | | 32.31 | | 11.82 | | 27.51 |
| # of clusters | 798 | | 493 | | 577 | | 339 | | 443 | |

## Table 7 Small business lending during Covid-19, Large vs. Small bank

This table reports the regression results analyzing how small business lending responds to COVID-19 as functions of bank size before the pandemic. The dependent variable is the growth of small business loans, the growth of C&I loans, and the amount of PPP loans scaled by total assets between December 2019 and June 2020 for each bank. *Bank exposure* is the weighted average of *Ln(Cases per Capita)* across counties in which a bank has branches, the weight is the share of deposits held by the bank in a given county. We measure bank size using either the log amount of total assets (*ln(Assets)*), or a dummy variable equal to one if a bank's total assets is below $1 billion and zero otherwise (*Small bank*). Bank Char. include ln(Assets), single-market indicator, liquid assets, equity ratio, tier 1 ratio, NPL, and ROA. Heteroskedasticity-robust standard errors are reported in the parentheses. "*" indicates statistical significance at 10% level, "**" at 5% level, and "***" at 1% level.

| | Small business loan growth | | | C&I loan growth | | | PPP loans | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Bank exposure | 0.040*** | 0.251*** | -0.018 | 0.024*** | 0.332*** | -0.045** | 0.005*** | 0.037*** | -0.000 |
| | (0.008) | (0.070) | (0.023) | (0.007) | (0.056) | (0.018) | (0.001) | (0.006) | (0.002) |
| ln(Assets) | 0.048*** | 0.155*** | 0.063*** | -0.018*** | 0.138*** | 0.013 | 0.002* | 0.018*** | 0.004*** |
| | (0.009) | (0.034) | (0.011) | (0.007) | (0.027) | (0.009) | (0.001) | (0.003) | (0.001) |
| ln(Assets)*Bank exposure | | **-0.017*** ** | | | **-0.025*** ** | | | **-0.003*** ** | |
| | | **(0.006)** | | | **(0.004)** | | | **(0.001)** | |
| Small bank | | | -0.316** | | | -0.309*** | | | -0.024* |
| | | | (0.143) | | | (0.112) | | | (0.014) |
| Small bank*Bank exposure | | | **0.063*** ** | | | **0.076*** ** | | | **0.005** ** |
| | | | **(0.024)** | | | **(0.019)** | | | **(0.002)** |
| Single market | -0.010 | -0.003 | -0.006 | -0.040** | -0.030 | -0.031 | -0.001 | -0.000 | -0.001 |
| | (0.022) | (0.022) | (0.022) | (0.019) | (0.019) | (0.019) | (0.002) | (0.002) | (0.002) |
| Equity | -0.826* | -0.829* | -0.798 | -0.931** | -0.937** | -0.895** | -0.014 | -0.014 | -0.011 |
| | (0.490) | (0.492) | (0.492) | (0.421) | (0.425) | (0.419) | (0.057) | (0.057) | (0.057) |
| ROA | -1.032 | -1.262 | -1.281 | 0.661 | 0.403 | 0.208 | -0.192 | -0.219 | -0.220 |
| | (2.098) | (2.110) | (2.100) | (1.755) | (1.763) | (1.745) | (0.215) | (0.215) | (0.215) |
| Tier 1 capital | 0.214 | 0.211 | 0.217 | 0.036 | 0.033 | 0.052 | -0.026 | -0.026 | -0.025 |
| | (0.242) | (0.243) | (0.242) | (0.163) | (0.164) | (0.162) | (0.021) | (0.021) | (0.021) |
| Liquid assets | -0.152* | -0.147 | -0.149* | -0.136** | -0.128* | -0.133* | -0.079*** | -0.078*** | -0.079*** |
| | (0.090) | (0.090) | (0.090) | (0.069) | (0.069) | (0.069) | (0.007) | (0.007) | (0.007) |
| NPL | -6.135*** | -6.121*** | -6.082*** | -7.085*** | -7.062*** | -6.995*** | -0.760*** | -0.757*** | -0.754*** |
| | (1.168) | (1.169) | (1.165) | (0.988) | (0.986) | (0.980) | (0.120) | (0.120) | (0.120) |
| Headquarter State FE | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 4,968 | 4,968 | 4,968 | 5,039 | 5,039 | 5,039 | 5,039 | 5,039 | 5,039 |
| Adjusted R-squared | 0.113 | 0.114 | 0.114 | 0.087 | 0.092 | 0.094 | 0.142 | 0.145 | 0.143 |

## Table 8 Local financial structure and employment resilience to Covid, differentiate by firm size

The table reports regression results of how employment respond to COVID-19 as functions of pre-pandemic share of small banks in local banking markets. The unit of analysis is at the county-industry-quarter-type level, there type represents whether firm size falls into [0,49], [50,499], or 500 and above. The analyses cover the period from 2019 Q1 through 2020 Q2. The dependent variable is the employment level relative to 2018 of each county. *Ln(cases per capita)* is the log of the number of confirmed COVID-19 cases per 100,000 people in a county by the end of each quarter. To measure the proportion of small banks in a county, we use *Share_small bank branches* or *Share_small bank deposits*. *Basic county control* includes the interaction of *Ln(cases per capita)* and *Income per capita*, *%65+ pop*, *Population density*, and *Unemployment rate*. Additional control includes the interaction of *Ln(cases per capita)* and bank concentration and county-aggregated bank characteristics (liquid assets, equity ratio, tier 1 ratio, non-performing loans, and ROA). Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses. ***, **, * denote significance levels at 1%, 5% and 10% respectively.

| | Employment | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ln(cases per capita) | -0.000814 | -0.00240 | 6.06e-05 | -0.00240 | 5.11e-06 |
| | (0.00108) | (0.00177) | (0.00252) | (0.00176) | (0.00250) |
| ln(cases per capita)*Firm size<50 | -0.00609*** | -0.00809*** | -0.00812*** | -0.00785*** | -0.00788*** |
| | (0.00126) | (0.00133) | (0.00134) | (0.00132) | (0.00132) |
| ln(cases per capita)*Firm size∈[50,499] | -0.00238 | -0.00116 | -0.00116 | -0.00125 | -0.00125 |
| | (0.00178) | (0.00186) | (0.00186) | (0.00183) | (0.00183) |
| share_small bank branches*ln(cases per capita) | | 0.000851 | 0.00104 | | |
| | | (0.00125) | (0.00131) | | |
| share_small bank branches*ln(cases per capita)*Firm size<50 | | 0.00388*** | 0.00385*** | | |
| | | (0.00120) | (0.00120) | | |
| share_small bank branches*ln(cases per capita)*Firm size∈[50,499] | | -0.00204 | -0.00207 | | |
| | | (0.00184) | (0.00184) | | |
| share_small bank deposits*ln(cases per capita) | | | | 0.00108 | 0.00141 |
| | | | | (0.00119) | (0.00126) |
| share_small bank deposits*ln(cases per capita)*Firm size<50 | | | | 0.00346*** | 0.00342*** |
| | | | | (0.00116) | (0.00116) |
| share_small bank deposits*ln(cases per capita)*Firm size∈[50,499] | | | | -0.00199 | -0.00202 |
| | | | | (0.00178) | (0.00178) |
| Basic county control | N | Y | Y | Y | Y |
| Additional control | N | N | Y | N | Y |
| County-Industry-Type FE | Y | Y | Y | Y | Y |
| State-Time FE | Y | Y | Y | Y | Y |
| Industry-Time FE | Y | Y | Y | Y | Y |
| Type-Time FE | Y | Y | Y | Y | Y |
| Observations | 502,117 | 490,710 | 490,424 | 490,710 | 490,424 |
| Adjusted R-squared | 0.702 | 0.703 | 0.703 | 0.703 | 0.703 |
| # of clusters | 2950 | 2860 | 2856 | 2860 | 2856 |