Banking Deserts and the Paycheck Protection Program

Abstract
The Paycheck Protection Program was a highly unusual policy measure enacted to provide bridge capital to support small businesses coping with the dramatic downturn in demand due to the COVID pandemic. By design, the program effectively required potential applicants work through the bank with whom they had a relationship. Yet large swathes of the country are effectively banking deserts, which dramatically steepens the gradient for those regions' businesses seeking Paycheck Protection Program support. This paper tests the proposition that the exogenous distribution of banks effectively discriminated against those regions where banking services are limited, while also looking at whether loans were distributed to those areas with less dense employment opportunities and higher concentrations of small businesses. We find that areas with fewer banking services and lower employment opportunities were systematically disadvantaged in Paycheck Protection Program distribution, while there were no significant flows to areas with higher rates of small businesses.

I. Introduction

For much of 2020, 2021, and 2022 to date, the COVID-19 pandemic has ravaged both the globe and the United States, harming both public health and the economy. As of early June, over 85 million people have been infected and over a million have died from the coronavirus in the US. While the unemployment rate is down to 3.6% in May 2022, after peaking at 14.7% in April 2020, GDP shrank through the first two quarters of 2020, creating the first official downturn since the Great Recession. The labor market has improved considerably in the meanwhile, with the economy now having a deficit of under a million jobs relative to the beginning of the pandemic. Yet the effects to public health and the economy have exposed many underlying inequalities within communities, between communities – particularly across the urban-rural spectrum – and more broadly, between regions of the country.

One such existing inequality is the access to banking services. Banking services vary regionally, creating inequalities in the ability to access credit between those banking clients residing in markets well-served and those under- or unserved. While many banking services can be transacted remotely via mobile banking and a rising fintech sector, there are still public and personal benefits derived from proximity to a bank branch or headquarters. Local banks are able to utilize “relationship lending” where “soft” information gleaned through business networks can be used for credit decisions (Berger and Udell, 2002; Petach, Weiler, & Conroy, 2021). These linkages are particularly important for rural small businesses that are informationally opaque, generating an imbalance of information to the disadvantage of the borrower based purely on geography (Akerlof 1970; Bunten, Weiler, Thompson, & Zahran, 2015; Conroy, Low, & Weiler, 2017).

The personal relationship that bankers can establish with small business owners provides the banks insights into a business’s managerial practices, its relationships with suppliers and customers, and its impact on the local economy among other pieces of information that are not included on the canonical balance sheet. Through bank consolidations and closures, many Americans live in a relative banking desert - a community with no physical banks – effectively creating spatial mismatches between financial resource conduits and the business sector. Even more live in areas that are effectively banking hinterlands, with no banking headquarters and served only by branches of national chains, as the distance between headquarters and branches has grown continuously since the turn of the millennium (Petach & Weiler, 2021). Areas may become dependent on branch locations from a single national commercial bank basing their lending on rigid policies, procedures, and credit scoring systems determined by a distant headquarters that do not incorporate the richness of soft information. The inequality in access to local banks can have significant implications on how recovery funds are distributed and thus for the trajectory of post-pandemic recovery, while also leaving a gap in the institutional leadership role that banks and bankers play in communities.

The COVID-19 pandemic caused many businesses to furlough or lay off broad swaths of employees as incoming revenues sharply declined, and businesses were forced to close by their local governments and people stayed home to prevent the spread of the virus. From February to April 2020 alone, the number of active businesses in the U.S. dropped 22% (Fairlie, 2020). Amidst these losses, in March 2020, Congress created the Paycheck Protection Program (PPP) to help struggling small business owners weather these unprecedented headwinds.

The Paycheck Protection Program allowed small businesses to obtain low-interest loans to cover payroll and other expenses. The loans were distributed through banks that were existing SBA 7(a) lenders. Originally $349 billion was allocated for the first-round of the program but given the severity of economic hardships experienced by small businesses, these funds ran out in two weeks. The second-round eased some of the constraints of the first effort, with a new tranche of $284.5 billion allocated on a first-come first-served basis. Having learned from the first-round experiences, the second allowed non-banks to request PPP funding, while also focusing more on smaller and more diverse businesses. In neither round were there specific allocations to particular banks. The system was national, as was the potential pot of money for disbursement.

We analyze both first- and second-round overall PPP lending patterns. Crucially, in the first-round, most of the funds were primarily allocated to those businesses that had an existing relationship with a qualified bank. Given the geographical distribution of local banks, this system for loan disbursement may have created greater overall inequality for those areas already experiencing inequality of banking access. The second-round opened the way for fintech loans, which removed some of the observed discriminatory practices and reduced the reliance on a relationship with a bank for gaining fund access.

Using data on the Paycheck Protection Program loan receipt and the locations of banking institutions, this study leverages national FDIC and NCUA data to understand how community banking density is related to the disbursement of Paycheck Protection Program loans. We first examine the a priori regional distribution of banks as well the distribution of businesses at the commuting zone level, using combinations of counties that represent a commuting shed. We then map the distribution of PPP loans relative to those distributions of establishments and banks. We will compare these results with measures of regional economic disadvantage – in particular the employment-to-population ratio, a particularly sensitive measure of labor market opportunity (Amior & Manning, 2018) – to see if the distribution of banking services and disbursements of PPP funds in fact mitigated or reinforced existing patterns of regional inequality.

Banking availability will be evaluated by measuring the number of banks per 10,000 population within a commuting zone using the USDA Economic Research Service 2000 definition. Commuting zones (CZ's), fully covering all 50 states and the District of Columbia, are a reflection of local labor markets and more accurately capture the accessibility of banks for establishments within a given region, following the intuitive proposition that business owners shop for banking services in the same geography in which they live and/or work. Banking hinterlands will be classified similarly, commuting zones without a bank headquarters. The focal dependent variable will be the number of loans per eligible small business establishment, although we will also briefly examine the amount of loans and jobs retained per eligible small business. The latter two variables are more likely to be programmatically tied to payrolls, while the more penetrating marginal decision by banks is how many loans to issue to small businesses.

The empirical framework analyzes a cross-section of all commuting zones, geographically situating banking deserts and hinterlands. There are three primary hypotheses to investigate, which will be introduced into the cross-sectional regression alongside a suite of regional control variables:

- PPP loans were systematically lower in relative banking deserts and hinterlands after accounting for lower business and population concentrations.
- Lower disbursements were more evident in areas that had lower employment-to-population ratios, indicating that loans were going to relatively advantaged labor markets.
- Small businesses of less than 50 as well less than 10 employees were not the major beneficiaries of the PPP program, despite the political rhetoric suggesting that such establishments were primary beneficiaries of the novel funding flows.

We include controls for income inequality, per capita GDP, educational attainment, and non-white share of the CZ's population, all of which may factor into regional loan flows.

The key hypotheses of the paper hold in the empirical analysis. Regions with higher concentrations of banks receive greater average numbers of loans, confirming the banking desert hypothesis. Furthermore, more loans per small business were disbursed in regions that had banking headquarters, even while controlling for the number of banks in the region, again affirming our a priori hypothesis. The number of loans did not go systematically to smaller businesses. Finally, loans were also lower in labor-market-challenged areas, as measured by employment-to-population ratios. In total, not only did smaller businesses not gain from the program, the fact that both the banking desert and banking hinterland hypotheses hold in conjunction with loans flowing to areas of job concentration suggest that there was indeed a spatial mismatch in the program based on geography.

The following section of the paper briefly reviews the related literature. The third section sketches the empirical model and data, with results elaborated in the fourth section. The fifth section concludes.

II. Related Literature

While the notion of banking deserts is anecdotally rich, there are remarkably few independent empirical analyses of the veracity and extent of the banking access problem. Most have found that the concept mainly applies to rural areas rather than cities (e.g. Hrushka, 2020; Kashian, Tao, & Perez-Valdez, 2015; Morgan, Pinovsky, & Perlman, 2018). This repeated theme reinforces the present work's focus on broader commuting zones (CZ's) rather than zip codes, census tracts, or counties as a preferred spatial level of analysis, given CZ's spatial homogeneity in uniting the transportation habits of residents and workers. A focus on metropolitan areas would also miss many of the more significant banking deserts and hinterlands. For the purposes of this paper, businesses are synonymous with business establishments.

Banking deserts are just one level of lack of bank access for businesses. The best banking relationships would develop where the borrower is in proximity of a bank headquarters rather than just a branch of regional or national chain. Credit score sheets created by faraway headquarters are not likely to match local circumstances and promising frontier businesses, hampering capital-led drives for regional employment growth and diversification (Conroy, Low, & Weiler, 2015). In contrast, areas with banking headquarters are more likely to have loan officers that can leverage soft information, improving estimates of loan viability. We therefore explore both banking deserts, commuting zones with no banks, and banking hinterlands, those commuting zones with no banking headquarters, as well as the overlap of this banking geography with the geography of non-white populations.

Given the newness of the topic, there have been limited studies of the PPP program, with most focusing on optimal allocation theory (Elenev, Landvoigt & Van Nieuwerburgh, 2020; Joaquim & Netto, 2020), bank performance (Granja, Makridis, Yannelis, & Zwick, 2020; Kapinos, 2021), flows to minority communities (Fairlie & Fossen, 2021), and/or business/employment survival (Bartik et Al. 2020; Autor et al., 2020). Yet the question of bank access and consequent local relationships is particularly important for this unusual business support policy, as banks were the sole conduit for securing PPP monies. Soft information is especially crucial in these circumstances, as the margins on PPP loans were very small (Marsh & Sharma, 2020). Banks thus had extra incentive to rely on soft information about the borrower to maximize the chance of the loan getting repaid. Again, the availability of such information is least likely in banking deserts, and less likely in banking hinterlands. Banks in such hinterlands are unlikely to have loan officers, while being more likely to use credit score sheets developed by distant headquarters.

Previous work on PPP and bank exposure indicates that there is a disconnect between the status of the local economy and likelihood of receiving PPP loans. Kapinos (2021) found that PPP loans did not systematically flow to counties that experienced unemployment surges in the first-round of the pandemic. More generally, using both ZIP code and county data, Granja et al. (2020) found little relationship between loan disbursement and local economic conditions; the extent of COVID cases was no better a predictor, with some indication that loans were actually more prevalent where caseloads were lower. In general, however, even this tremendously comprehensive study was somewhat limited by its choice of geography, focusing on ZIP codes and counties, neither of which are natural markets. Fairlie and Fossen (2021) similarly used ZIP codes in their analysis, which we believe represents too small a microscope to properly understand PPP disbursement.

In contrast, this paper relies on commuting zones as its primary geographic scale of analysis, as these define the extent of commuting and intra-regional cohesion (Amior & Manning, 2018). Buyers of loans are most likely to choose banks that are either close to home or workplace. In terms of the status of the local economy, we focus on the employment/population ratio as an indicator of the density of jobs available to the region's population following the significant downturn in March/April 2020, as well as the proportion of citizens with a higher-education degree and per capita GDP. Amior and Manning underscore the employment/population ratio as being a particular appropriate measure of economic opportunity, which we leverage in this work.

Our approach follows clues left by the handful of studies on PPP loan distribution. Amiram and Batteti (2020) and Li and Strahan (2020) indeed find those establishments with existing banking relationships tended to get loans first and in the largest amounts. We indirectly test both propositions in the present work, in particular through the resource flows channeled towards the smallest businesses which are less likely to have established banking relationships. Granja et al. (2020) further find that those relationships tended to outweigh stated goals of the program, namely targeting those areas and businesses in greatest need of loans due to the pandemic. Barrios, Minnis, Minnis and Sijthoff (2020) finding that establishment payrolls closely predict PPP loan receipt indicates that there may be a positive relationship between business size and loan disbursement, which we test empirically as well. Finally, Fairlie and Fossen (2021) find that early loans went mainly to non-minority applicants, while the later tranche flowed more to these marginalized populations. We follow their lead in testing the significance on non-white shares of CZ populations on loan disbursement.

As previous work has demonstrated, the implications of systematic informational asymmetries based on geography can fundamentally shift innovation and resources away from lagging regions, further entrenching their economic struggles (Weiler, 2000). These geographic information asymmetries (GIA) are most likely to be felt in business-to-business transactions built on the supplier's understanding of those demanding services. Small business lending may be particularly vulnerable to GIA discrimination, given its reliance on credit scoring developed at a bank's headquarters – which may not be congruent with the realities of a rural economy – as well the past viability of similar projects. The latter will be a particularly high hurdle for innovative projects that have no track record in the focal economy. Rural areas tend to have thin informational markets due to lower establishment dynamism and thus fewer datapoints from which to extract the viability of loans (Bunten et al, 2015).

Statistically, the perception of otherwise identical probability distribution of outcomes in two regions will be skewed towards the market with thicker information through greater past business experience. In contrast, the thin market featuring fewer datapoints will lead to higher perceived variance of outcomes, heightening uncertainty and thus risk for bankers (Weiler, Hoag, & Fan, 2006). These risks may deter bankers from making loans to those companies without existing intensive relationships, leading to disproportionate flows towards advantaged regions and businesses. These informational asymmetries may thus be a driving force for systematic discrimination of PPP loans towards those thick-market regions that have denser labor markets as measured by the employment/population ratio, established banking networks, and larger establishments. Our empirical work tests these propositions.

III. Data and Empirical Model

Data on Paycheck Protection Program loans come from the Small Business Administration. These data contain information on all individual loans distributed through the program's first phase which originally ended June 30, 2020 but was extended to August 8. The loan amount, business address, number of jobs reported, date the loan was approved, and demographic characteristics of the business owner are included for each approved loan. For our work, the loan amount, number of jobs reported, and business address are used in the construction of the final data. The demographic characteristics are not used due to the large amount of loans where those questions were unanswered and the likelihood of introducing sample selection bias through their use.

Commuting Zones (CZs), from ERS's 2000 delineations, are the primary unit of analysis. CZs offer two main advantages over other geographic delineations. First, CZs better represent local economies better than other political boundaries by grouping counties together which have strong commuting-ties. Second, CZs contiguously cover the continental United States meaning that all businesses which received a PPP loan will be retained in our sample. Commuting Zones also lend themselves particularly well to studying the distribution of PPP loans. It is conceivable that a small business may have to seek banking services outside of its city or county due to a lack of access to banks in that location. Using CZs as the geographic unit will more accurately capture the number of banks available to a small business. To obtain a measure of the number of loans in a CZ the number of loans are first aggregated to the zip code level. These zip codes are then mapped to the counties in which they reside, and for the zip codes which cross county borders, the number of loans is weighted by the proportion of businesses that reside each county[1]. The aggregate number loans at the county level are then mapped to the appropriate CZ. This process is repeated for both the amount of loans and the number of jobs reported to get commuting zone measures for these outcomes.

Commuting zones are geographically diverse, do not have identical populations, nor identical economies. For this reason, we normalize our outcomes of interest by the number of small businesses in each CZ. We focus on the number of small businesses in each CZ since the Paycheck Protection Program was designed to provide economic relief for small businesses. The Small Business Administration definition of a small business varies by industry, so we utilize a more general definition of a small business adopted by the Small Business Administration — a business with fewer than 500 employees. To get the number of businesses with fewer than 500 employees, we use data from the most recent County Business Patterns from the U.S. Census Bureau. We implement the same aggregation procedure to get the total number of small businesses for every CZ.

Our main source of commuting zone-level economic characteristics, such as population, household income, demographic characteristics, and level of education, is from the American Community Survey 5-year estimates for 2015-2019. This source provides data on these characteristics at the county level which are then aggregated up to the CZ level. Data on county GDP comes from the Bureau of Economic Analysis Regional Economic Accounts and summed up to CZ GDP. These data are for 2019 since that is the most recent data available at the county level. Data on the number of COVID-19 cases comes from The New York Times which has been tracking the number of daily COVID-19 cases by county since the beginning of the pandemic. To accurately measure the impact of COVID-19 cases and potential local lock-down measures in an area, we use the cumulative count COVID-19 cases for each county on April 3, 2020, which is when the program opened for small businesses. The county case count is then aggregated up to the commuting zone. We get our data for labor market outcomes from the Bureau of Labor Statistics' (BLS) Local Area Unemployment Statistics. Since the BLS measures employment in first two weeks of the month, we use the county data on employment from April 2020 since these data reflect the reality of local labor markets when business establishments were deciding whether to apply for a PPP loan.

We obtain our data on bank location from two sources: Federal Deposit Insurance Corporation (FDIC) and the National Credit Union Administration (NCUA). We focus on both banks and credit unions because both were authorized to provide PPP loans to small businesses. We obtain the location of all bank branches and headquarters from the FDIC's Institutions and Locations database. This provides the addresses of all federally insured banks, county of banks location, the service type of banks, and whether the bank is the main office or a branch location. We create a measure of total banks by including all full-service banks, both brick and mortar and retail locations, as well as permanent limited-service banks that only accept deposits and payments. We include the latter type of banks to capture the effect of banking hinterlands on the distribution of PPP loans. The county data is again aggregated up to the CZ level. The NCUA Quarterly Call Report Data for the second quarter of 2020 are used to get a list of all credit unions by location. Credit Unions are only listed by address without their county of residence, so we follow a similar zip code to county procedure as with the PPP loan data before we aggregate these to the commuting zone. The number of credit unions are combined with the number of banks to create a total measure of bank concentration for each CZ.

Table 1 presents summary statistics for each of the variables in our sample. The final sample consists of 706 commuting zones. Due to the structure of the program, we only have data for loans that were made during its first two iterations in early to mid-2020. To account for population differences across CZs, we normalize the number of banks and credit unions, bank headquarters, COVID-19 cases, and number of small businesses by CZ population per ten thousand in regional population – again in the spirit of Amior and Manning (2018).

[Table 1 about here]

To explore the geographic distribution of PPP loans, banks, and COVID-19 cases, we map the quintiles for data for each in Figure 1. Panel (a) shows the geographic distribution of the number of PPP loans per small business, Panel (b) shows the geographic distribution of banks per 10,000 people, and Panel (c) shows the geographic distribution of the number of COVID-19 cases per 10,000 people. The amount of PPP loans per small business are the highest in the central United States, stretching from North Dakota to the northern portion of Texas. This region shares significant overlap with the geographic distribution of banks per 10,000 people. The Southwest also has a high number of PPP loans per small business, however there is not a high concentration of banks in this region. COVID-19 per 10,000 cases as of April 3rd 2020 are concentrated in the northeast United States, Louisiana, and the Southwest.

[Figure 1 about here]

This geography aligns with where the largest outbreaks of cases were near the beginning of the pandemic. The highest quintile for COVID-19 cases has a very large range (3.52 - 88.29), making some areas appear to have a comparable number of cases despite having much different values of cases per 10,000 people. Overall, these maps suggest that there is significant overlap between the regions where the number of PPP loans and the number of banks is the greatest.

There is some overlap between loans and COVID-19 cases, but it does not appear from these maps that the PPP loans went to where COVID-19 cases were the greatest. It is possible that the heterogeneity in the intensity of the stay-at-home orders and business closures near the beginning of the pandemic did not align with where the cases were the highest at the start of the PPP program.

To explore these and other relationships further, we now turn to a more formal analysis. We seek to answer whether the distribution of banks and banking hinterlands partially determined the distribution of PPP loans. Since the PPP loans were distributed through banks and a limited amount of initial funds, we hypothesize that regions with a greater concentration of banks as well as bank headquarters received more PPP loans, and that banking deserts and banking hinterlands were systematically disadvantaged in PPP allocations. We take the geographic distribution of banks as being given a priori, and thus exogenous to the analysis. A higher concentration of banks provides more opportunities for small businesses to find a bank that had not already exhausted their allotment of PPP funding. Although the program was originally designed to continue through June 30, 2020, the original amount of funding provided by the CARES Act ran out by April 16, 2020. Businesses in regions with a higher concentration of banks that were able to access the PPP funds earlier likely increased their likelihood of survival, in line with Bartik et a.l (2020) and Autor et al. (2020). We are specifically also interested in whether loans, amounts, and job retained went to the small businesses that were avowedly priorities for the program. To empirically test these hypotheses, we estimate the following equation:

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\begin{aligned}
Y_i = \beta_0 &+ \beta_1 BankConcentration_i + \beta_2 BankConcentration_i^2 + \beta_3 BankHQs_i \\
&+ \beta_4 BankHQs_i^2 + \beta_5 Cases_i + \beta_6 NonWhiteShare_i \\
&+ \beta_7 ShareSmallestBusinesses_i + \beta_8 \frac{Emp.}{Pop.}_i + \beta_9 \frac{HH.Med.Income}{HH.Mean.Income_i} \\
&+ \beta_{10} perCapitaGDP_i + \beta_{11} BAPlusShare_i + \epsilon_i
\end{aligned}
$$

where Y_i is the outcome of interest — either the number of PPP loans per small business, amount of PPP loans per small business, number of jobs reportedly retained per small business, or their first-round of funding equivalent in commuting zone i. $BankConcentration_i$ is the number of banks and credit unions per 10,000 people in CZ i, $BankMainOffices_i$ is the number bank main offices per 10,000 people in CZ i, $Cases_i$ is the commuting zone number of COVID-19 cases per 10,000 people, $NonWhiteShare_i$ is the share of non-White population in CZ i, $ShareSmallestBusinesses_i$ is the CZ-level share of businesses that have fewer than 50 or fewer than 10 employees out of all small businesses, $\frac{Emp.}{Pop.}_i$ is the commuting zone-level employment-to-population ratio for April 2020, $\frac{HH.Med.Income}{HH.MeanIncome_i}$ is a commuting zone-level measure of inequality measuring the ratio of household median income to household mean income, $perCapitaGDP_i$ is the per capita GDP of CZ i, $BAPlusShare_i$ is the share of the CZ population that has at least a bachelor's degree, $SmallBusinessConcetration_i$ is the number of businesses with less than 500 employees in CZ i, and ϵ_i is an idiosyncratic error term.

Variance Inflation Factor (VIF) analyses indicate that there was no substantive multicollinearity among the explanatory variables. We fully acknowledge that the cross-sectional dataset can offer only a limited view of PPP impacts, given that the data show only transacted loans. The lack of application data would tend to upwardly bias the findings by overstating the effect of local banks, making our results an upper-bound of the PPP effect.

Coefficients β_1 and β_3 are our main coefficients of interest. Consistent with our banking desert and banking hinterland hypotheses, we expect both coefficients to be positive for all outcomes of interest, as more loans flow to those areas with more banks and more bank headquarters rather towards banking deserts and hinterlands. We include the square of both of these variables to account for the possibility that the concentration of banks and bank headquarters beyond a certain threshold does not further increase the outcomes of interest. As discussed in the introduction and literature review, we also focus on the employment/population ratio as a particularly important measure of labor market opportunity, and thus have a keen interest in β_8. If funds had flowed to more distressed labor markets in the wake of the COVID crisis, we would expect β_8 to be negative. However, if funds in fact went to relatively advantaged labor markets, β_8 would be positive. In that sense, β_8 becomes an especially useful bellwether in determining whether PPP in fact served the most economically distressed regions, as well as acting as a control for business activity in the region.

Additionally, we are interested in three sub-questions: (1) whether PPP loans went to areas that were most affected by the pandemic, (2) whether commuting zones with a higher proportion of non-white population received fewer loans, and, in particular, (3) whether the smallest small businesses were particularly disadvantaged in accessing PPP loans. For these questions, we are interested in coefficients β_5, β_6, and β_7 respectively. If PPP funds were distributed to the commuting zones that were most affected then we would expect β_5 to be positive, if communities of color had a harder time accessing or applying for PPP funds then we would expect β_6 to be negative, and finally, if the smallest businesses were particularly disadvantaged in access or applying for PPP loans then we would expect β_7 to also be negative.

IV. Results

a) PPP Program in Total

Table 2 presents results from estimating the effect of bank concentration on the number of total first- and second-round PPP loans. Column 1 reports the results for the number of loans per small business in a commuting zone, Column 2 reports the results for the loan amounts per small business, and Column 3 displays the results for the number of jobs retained per small business. Coefficients are standardized to impacts in terms of standard deviation changes in the dependent variables in response to a one standard deviation change in the focal explanatory variable; the Appendix reports all results in non-standardized formats. We also apply two different measures for the share of smallest businesses: one where we define smallest businesses as businesses with fewer than 10 employees and a second as businesses with fewer than 50 employees. Results using each of these measures are largely similar, so we focus on those businesses with fewer than 10 employees and reserve the specifications with the alternative measure for the appendix.

[Table 2 about here]

These results suggest that larger concentrations of banks and credit unions in a commuting zone had a positive and statistically significant impact on the number of PPP loans per small business. Commuting zones where the number of banks per 10,000 people is one standard deviation greater see an increase in the number of PPP loans per small business of PPP loans per small business by about 1 standard deviation. There appears to be diminishing returns to increasing the number of banks per 10,000 people, however, given the negative coefficient on the squared term. Once the concentration of banks is greater than 23.3 banks per 10,000 people, the number of PPP loans is negatively affected by additional banks. Even before that level, each additional increase in the concentration of banks is less effective in increasing the number of PPP loans. This result suggests that in places that have fewer banks per 10,000 people, an additional bank is helpful for obtaining a PPP loan, but that in places that already have a higher concentration of banks, additional banks actually reduce the number of loans.

These findings indicate that the geographical distribution of banks is impacting the number of PPP loans, likely by providing more options to small businesses to apply for a loan. If one local bank was no longer accepting applications for the funds, the small business could look to another bank in their area to apply. Small businesses in areas with fewer banks did not have this luxury. Areas with a sufficient number of banks were not helped by additional banks, with such markets having sufficient bank saturation to handle PPP loan demand.

We find similar first-order effects for the number of banking headquarters per 10,000 people; commuting zones with a concentration of headquarters that is one standard deviation greater received 33.5%-35% of a standard deviation more PPP loans per small business. However, we do not find diminishing returns to the number of bank headquarters; more bank headquarters systematically increase the number of loans. Bank headquarters are likely to have a greater ability to specifically tailor loans by leveraging soft information, creating an advantage for small businesses located in CZs with a bank headquarters over small businesses located in CZs with simply a branch office. These results are stable across both specifications accounting for different definitions of the smallest businesses.

In addition to our main hypotheses about the geographic locations of banks, we are also interested in whether the PPP funds went to areas that were the most affected by the pandemic. Commuting zones with more COVID-19 cases per 10,000 people received more loans. Places where COVID-19 cases per 10,000 people that are one standard deviation above the mean decreases the amount of loans received by 5.2% of a standard deviation all else equal. In the early stages of the pandemic, regions that had more cases were likely to have more restrictions on the types of business which could remain open. Our empirical results in fact suggest that loans were going to CZs that were in greater health distress. Regions that had a greater employment-to-population ratio of one standard deviation also received about a 20% of a standard deviation greater share of PPP loans, indicating that PPP loans went to regions that generally had advantageous labor market conditions. We also ran the models using March 2020 employment data, which gave substantively identical findings.

It is worth noting that more economic activity in a CZ makes the demand for loans greater, so in some sense the employment/population ratio is more of a control for economic activity in the form of demand for PPP loans. More economic activity means more loans, ceteris paribus. However, this control also makes the banking result especially stark and compelling, in that the equation has already controlled for potential business loan demand.

While the Paycheck Protection Program was not designed to specifically help minority-owned small businesses, we do find that regions with a greater share of non-white population received a larger amount of PPP loans per small business. A one standard deviation larger share of non-white population received about 16% of a standard deviation more PPP loans per small business. This finding is consistent with the findings in Fairlie and Fossen (2021), and is important because minority-owned businesses were some of the most affected businesses by the economic shutdown (Fairlie, 2020).

We were also interested in whether the smallest small businesses were disadvantaged by the PPP loan process. For this query, we created two different measures to represent the share of the smallest small businesses in a commuting zone: one for the share of business with fewer than 10 employees out of all small businesses and one for small businesses with fewer than 50 employees. We find that CZs with a greater share of small businesses with fewer than 10 employees and fewer than 50 employees did receive fewer PPP loans. Places with a one standard deviation higher concentration of businesses with fewer than 10 employees received 14.8% of a standard deviation fewer PPP loans and places where the concentration of small businesses with less than 50 employees was one standard deviation greater also received about 15% of a standard deviation fewer PPP loans (Table A6).

Next, we turn to whether the geographical distribution of banks and banking headquarters affected the amount of the loans distributed to commuting zones in and the number of jobs that were reportedly saved with the PPP loans . Since the amount of PPP loans per small business and the number of jobs retained per small business is a function of the number of loans in a CZ, we add this as a control to equation 1. Column 2 of Table 2 presents the results for the PPP loan amount per small business and Column 3 presents results for the number of jobs retained per small business.

We find that the geographic distribution of banks and credit unions did not have a significant impact on the amount of the PPP loan per small business. Similarly, we do not find that the concentration of banks and credit unions had a significant effect on the number of jobs retained per small business. These results make intuitive sense since banks did not determine the amount of loan that small businesses were able to receive. Both outcomes are dependent on the first being approved for a loan, so it makes sense that neither are affected by the distribution of banks. The amounts of loans and jobs saved were strictly a function of the business itself, not the PPP policy.

b) First-Round of PPP

The Paycheck Protection Program was originally designed to be in effect from April 3 to June 30, 2020, but it ran out of funds by April 16, and it was unclear if more funding would be approved. The magnitude of the economic impacts of the beginning of the pandemic meant that missing out on this first-round of funding could impact the survival of small businesses that were affected by the government-imposed lockdown orders. For these reasons, we examine whether the concentration of banks impacted the receipt of these first-round loans. We present the findings in Table 3.

[Table 3 about here]

Once again, we find that greater concentrations of banks and credit unions increased the number of PPP loans per small business. Areas with a one standard deviation positive difference in the number of banks and credit unions per 10,000 people raised the number of first-round PPP loans nearly 1 standard deviation. This is again subject to diminishing returns as in the full sample of PPP loans, with a lower threshold at 20 banks per 10,000 people. We also find that bank headquarters were also an important determinant of the number of PPP loans per small business. Commuting zones where the concentration of bank headquarters per 10,000 people was one standard deviation greater than another commuting zone received 39.7% of a standard deviation more PPP loans per small business. In the first-round of the program, this result is also subject to diminishing returns. This finding highlights the importance of bank access in the distribution of these loans. Small businesses that are in commuting zones with more banks were able to access funds earlier than small businesses that were in relative banking deserts and banking hinterlands.

While not a specific aim of the program, we also find that these early loans were not distributed to regions that were the most affected by the pandemic The pandemic was the core of the crisis, so evaluating how well the program fared in combating that crisis is an interesting question. Fewer loans went to regions with a higher concentration of COVID-19 cases and to regions where the employment-to-population ratio were lower. During the first-round of funding areas with COVID-19 cases per 10,000 that were one standard deviation greater received fewer loans per small business by 3.5% of a standard deviation. Commuting zones with an employment-to-population ratio that was one standard deviation higher received about 22% of a standard deviation more loans per small business. Regions with fewer cases per person were likely not under as severe lockdown restrictions as regions where the virus was spreading more broadly, and businesses were able to continue operating at a closer to normal capacity. Similarly, regions with a greater employment-to-population ratio and thus deeper job markets may not have been experiencing the same pandemic induced layoffs but still received a greater share of these first-round loans. At the time it was unclear whether there would be more support for small businesses, so these results represent a serious shortcoming of the program by advantaging areas with stronger labor market conditions.

In the first-round of PPP the smallest businesses were disadvantaged compared to their large counterparts. Increasing the share of small businesses with fewer than 10 employees by one standard deviation decreased the number of first-round PPP loans per small business by over 15.5% of a standard deviation. We find a similar result when we expand our definition of the smallest businesses to those with fewer than 50 employees (12.2% of a standard deviation fewer loans Table A6). This highlights that the smallest businesses, which were likely to be most in need of the additional support, had unequal access to economic relief. We do not find that CZs with a higher proportion of non-white residents also received more of these first-round funds. Combined with the results from the full set of PPP loans, this finding suggests that small businesses in regions with a higher proportion of non-white people had to wait longer to receive PPP funds, a finding consistent with the results in Fairlie and Fossen (2021), Atkins, Cook, and Seamans (2021), and Garcia and Darity (2022).

In Table 3 we also examine whether the geographic distribution of banks affected the amount of these first-round loans and the number of jobs these loans helped retain in Columns 2 and 3, respectively. Similar to our previous results using the full set of PPP loans, we do not find many significant results for these outcomes using just the first-round of loans. For the first-round of PPP loans, banks and credit unions do not affect the amount of PPP loans nor the number of jobs retained per small business. The number of bank headquarters does impact the loan amount per small business and the number of jobs retained per small business for the first-round loans. Commuting zones with a one standard deviation positive difference in the concentration of bank headquarters received loan amounts that were 20.9% of a standard deviation greater and retained 36.4% of a standard deviation more jobs. Above a certain concentration, however, these outcomes were hurt by having a greater concentration of bank headquarters. COVID-19 cases and the share of non-white population also do not impact the amounts or jobs retained of the first-round PPP loans. All of these findings are likely attributable to the applications process. The amount of the loan and the number of jobs it was used to retain are not determining factors for loan approval, so once the loan is approved, these factors no longer influence these amount and job outcomes.

We do find that a higher CZ employment-to-population ratio does correlate with a greater number of first-round loan amounts and jobs retained per small business. Increasing the CZ employment-to-population ratio by one standard deviation raised the first-round loan amount by 31.8% of a standard deviation. The same difference in the employment-to-population ratio raised the number of jobs retained per small business by 26.2% of a standard deviation. Commuting zones with more employment received more first-round loans and therefore received a greater share of the total amount available and were able to retain more jobs. As has now been consistently shown, this finding suggests that larger loans went to areas with relatively strong labor markets, potentially increasing inter-regional inequality

c) PPP Loans by Bank Type

Thus far we have treated all banks and credit unions as the same. However, there is heterogeneity across bank type with each having a slightly different method of doing business. For example, banks and credit unions offer many of the same financial services, but credit unions are non-profit entities and banks are for-profit. Within banks there are differences as well, with community banks operating differently than national banks. To capture how these differences affect the distribution of PPP loans, we adjust our measure of banking deserts to include the concentration of credit unions and the concentration of banks separately in the second column of Table 4. In Column 3, we further disaggregate the banking concentration measure into the concentration of community banks and non-community banks alongside the concentration of credit unions. We do this for both the full sample of PPP loans as well as the sample of first-round PPP loans in Table 5.

[Table 4 about here]

In the full sample of PPP loans we find that it is a higher concentration of banks that affects the distribution of PPP loans and not the concentration of credit unions. Places where the concentration of banks is one standard deviation greater is correlated with places where the number of PPP loans per small business is 1.03 standard deviations higher. The marginal impact of an additional bank is lower with each additional bank. We do not find that places with a greater concentration of credit unions increase the number of PPP loans per small business. We also find that the type of bank matters for the distribution of PPP loans. Both greater concentrations of community banks and non-community banks lead to more PPP loans per small business, but an increased concentration of community banks has a greater impact on the number PPP loans distributed. Commuting zones where the concentration of community banks in one standard deviation greater are associated with a 1.171 standard deviation increase in the number of PPP loans and places where the concentration of non-community banks was one standard deviation greater are associated with a 0.367 standard deviation more loans per small business. Both community and non-community bank concentration are subject to diminishing returns of an additional bank.

[Table 5 about here]

We also account for the heterogeneity in bank concentration for the sample of first-round loans. Results for the first-round of PPP loans accounting for differences in type of bank concentration are included in Table 7. We find similar results for the first-round of PPP funding. Places with a banking concentration that is one standard deviation greater receive 94.7% of a standard deviation more first-round PPP loans. During the first-round of funding credit unions also played a significant role in the distribution of PPP loans to small businesses: CZs with a credit union concentration one standard deviation higher saw 14.7% of a standard deviation more round one loans. There was much uncertainty at the beginning of the pandemic in regard to lockdowns and the resulting potential economic fallout. This resulted in a scramble to apply for and obtain a PPP loan for small businesses. Since funds were much more limited, having more banking services available regardless of type mattered more than in the full sample of loans.

Similar to our other analyses, we find that each additional bank and credit union has less of an impact on PPP loan distribution. We again further separate out the community banking concentration from the previous bank concentration measure and find again that an increased community bank concentration has a larger impact on loan distribution than non-community bank concentration. Places where the concentration of community banks is one standard deviation high saw 1.15 standard deviation more loans while places where the concentration of non-community banks was one standard deviation greater saw only 18.1% more loans. Greater credit union concentration is also factor that impacted the distribution of PPP loans when accounting for the different types of banks and is correlated with 0.099 standard deviation more loans. These results suggest that the existence of more financial institutions in a CZ impacted the distribution of PPP loans with banks, especially community banks, having the greatest impact in the First-Round.

Overall, we find that the type of bank matters. In both the full PPP sample and the first-round sample of loans we find that banks affected the distribution of PPP loans more than credit unions did. When we examined banks more closely and looked at the effect of community banks separately, we found that a greater concentration of community banks had the largest effect on the distribution of PPP loans. Community banks focus their services in a much smaller geographic region than non-community banks. This focus gives small businesses in the banks' catchment area a better chance of obtaining a loan since there is less competition from other businesses from farther away, which helps explain why community banks had the greatest impact on the number of loans in a CZ.

d) Second-Round of the PPP

The Paycheck Protection Program was an evolving policy. After the initial allocated funds were exhausted, the program was re-authorized and nearly $300 billion more funds were added to for potential loans. Along with the additional funds came some changes to how the program was implemented, in an attempt to make it easier for small businesses to get the help they needed to survive through the early stages of the COVID-19 pandemic. The changes in the second-round of PPP funding included prioritizing the smallest businesses as well as expanding the pool of authorized lenders to include more non-traditional lenders.

To ensure that our main results are not being driven by the loans made during the first-round of program funding before these changes, we use a subset of PPP loans that were made after April 27th, when the second-round of funding went into effect. Using this sub-sample of loans, we test whether banking concentration affected the number of loans distributed in a CZ, the dollar amount of PPP loans in a CZ, and the number of jobs retained in a CZ. We also examine whether our secondary hypotheses were impacted by changes in the program. The first column of Table 6 presents our findings for the number of loans.

[Table 6 about here]

Even after the changes to the Paycheck Protection Program, bank and credit union concentration is still an important factor for the number of loans distributed in a commuting zone. CZs where the number of banks per 10,000 people is one standard deviation greater increases the number of loans per small business by around 70% of a standard deviation. This impact is less than the impact we found when using the full sample of PPP loans or the just the first-round of PPP loans (about 1 standard deviation increase in the number of PPP loans per small business). There are still diminishing returns to increasing the number of banks per 10,000 people, but in the second-round of loans the impact of an additional bank greater in the second-round of loans than in the full sample of loans. Overall, commuting zones with more banks received more loans than places with fewer in the second-round of the PPP.

In contrast to the full sample of PPP loans and the first-round sample of loans, banking headquarters did not impact the distribution of PPP loans in the second-round. In the full sample and first-round, increasing the number of banking headquarters by one standard deviation increased the number of PPP loans per small business by 0.333-0.414 of a standard deviation. When just the second-round loans are used, the impact of a standard deviation increase is no different than 0. This suggests that the effect for banking headquarters is entirely driven by the first-round of the program. One possible explanation for the difference in findings is that after the first-round, non-headquarter banks were able to adjust their practices and make more loans despite not being a main banking office, decreasing the importance of having a higher concentration of bank headquarters in a commuting zone.

When examining areas with more advantaged labor markets, we find that in the second-round of loans these advantages labor markets were not necessarily receiving more loans than other less advantage labor markets. Places where the employment to population ratio is one standard deviation higher received only 0.103 of a standard deviation more PPP loans per small business. This is less about half the magnitude than the same effect in the full sample of PPP loans and lass than half the effect when compared to just the first-round loans. However, this result is only significant at the 10 percent level and is sensitive as to which measure of small business we include. This suggests that more second-round loans went to places that had were not as economically advantaged and may have had more pandemic related layoffs.

Commuting zones which had a greater share of the smallest businesses (those with fewer than 10 or 50 employees) still received fewer loans than CZs that did not have as high of a share. Places where the share of businesses with less than 10 employees is one standard deviation greater decreases the number of loans per small business by 9.6% of a standard deviation and a similar difference in the share of businesses with less than 50 employees results in a decrease of 13.3% (Table A7) of a standard deviation. This suggests that in the second-round of the program the smallest businesses were still disadvantaged compared to their larger counterparts. Even though CZs with more of the smallest businesses were more disadvantaged, they fared better than in the first-round as the impact for each measure of the smallest businesses is lower than in the other samples.

When looking at our secondary hypotheses regarding the share of non-white population and the prevalence of COVID-19 cases, we also find that the changes in the program before the second-round resulted in improved outcomes. In the first-round of the PPP, places with a greater non-white population were not statistically different than CZs with less of a non-white share, but in the second-round places with a share of the non-white population that is one standard deviation greater than another CZ received around 20% of a standard deviation more PPP loans. The changes to program prior to the second-round appear to be driving the result in the full sample of loans. Similarly, in the first-round of the program, loans went to places that were not as affected by the pandemic. Places where the caseload was greater actually received fewer loans in the initial funding of the program. When just the second-round of the program is considered, more loans went to places where the caseload was greater. Places where the caseload was one standard deviation greater received about 13% of a standard deviation more PPP loans per small business.

These results suggest that the adjustments made to the program before the second-round did impact the distribution of loans. The impact of a greater concentration of banks in a CZ is lower than in the full and first-round samples. The importance of bank headquarters is diminished in the second-round sample as well. These second-round loans also went to places with a greater non-white share, and places that were more affected by the pandemic.

e) Fintech Sample

One of the changes that occurred in the second-round of PPP funding was allowing more fintech companies to make PPP loans. Fintech lenders are lenders which use technology and automation to deliver financial services. The change to allow more fintech companies make PPP loans was also an important program modification to make it more accessible to more small businesses. Since fintech lenders rely more on technology and automation, permitting them to make loans negates some of the advantages that businesses in CZs with a high bank concentration have. Small businesses in relative banking deserts could apply for a PPP loan through remote services offered by these fintech lenders despite being geographically distant from the lender's physical location. The automated decision process employed by the fintech companies for these loans also removes relational lending advantage small businesses in areas of high bank concentration enjoy. These features may make the inclusion of fintech lenders an especially important change to the PPP.

We test whether the inclusion of fintech companies impacted the geographic distribution of loans by limiting the main sample of PPP loans to just second-round PPP loans made by fintech companies. We rely on the list of fintech companies that made PPP loans from Howell et al. (2022) and match the lenders in the full PPP data to the list of fintech companies. This leaves use with a sample of 728,117 PPP loans, which we then assign to CZs as before using the address of the small business. We then test whether the geographic distribution of banks impacted this sample of loans made by fintech companies. Results are presented in Column 2 of Table 6 for the number of loans per small business.

When only loans from fintech companies are included, we find that places with higher concentrations on banks no longer receive more PPP loans per small business compared to places with lower banking concentrations. In fact, we find that these fintech loans were distributed to commuting zones with lower concentrations of banks. Commuting zones where the number of banks per 10,000 people was one standard deviation lower received 63.4% of a standard deviation more loans. These results make intuitive sense. Small businesses in commuting zones with more banks had more options for obtaining a PPP loan whereas small businesses in banking deserts did not have many local options, or they may not have had a prior relationship with their local banks making PPP loan approval more difficult. The features of fintech lenders, particularly the ability to apply for a loan remotely, made it easier for small businesses to apply for and obtain a loan. Commuting zones with fewer banks per 10,000 people benefit from the existence of fintech loans when the bank concentration is low. Once the concentration of banks exceeds 19 banks per 10,000 people the CZ receives fewer fintech originated PPP loans. This is likely because there are more traditional banking options in those CZs and small businesses do not need to rely on the fintech lenders as much. When examining the effect of the distribution bank headquarters we do not find that their geographic distribution affects the number of loans made by fintech companies in a commuting zone.

Unlike in the other PPP loans samples that we use, the loans made by fintech companies did not go to small businesses in commuting zones with relatively advantaged labor markets. The effect of a greater employment to population ratio is statistically indistinguishable from 0. PPP loans that originated from traditional banks did tend to go to areas that had higher employment to population ratios. This suggest that fintech loans were not going to places that already had a labor market advantage. We also find that unlike in other samples, the smallest small businesses, those with fewer than 10 employees, were not disadvantaged when focusing on PPP loans made by fintech companies. When we expand our definition to include small businesses with up to 50 employees, we do find that CZ with a greater share of these businesses were still at a disadvantage in receiving a loan from a fintech company. CZs where the share of these businesses is one standard deviation greater received 0.173 of a standard deviation fewer loans. This effect is even stronger than in the other samples of loans. The difference in between the samples could be from how these businesses are geographically distributed. More businesses with less than 50 employees could be located in CZs with higher bank concentrations, which also received fewer fintech loans.

We also find that places with a greater share of non-white people received more loans that originated from fintech lenders. Commuting zones with a non-white population share that is one standard deviation higher receive approximately 22% of standard deviation more fintech PPP loans. Our finding is consistent with the results in Howell et. al (2022) which finds that Black-owned businesses received more loans from fintech companies than other from other types of lenders. This effect is greater than in the other samples of PPP loans that include loans from traditional banks, which suggests that this change to the program was the greatest factor affecting the distribution to CZs with a greater non-white population share.

More fintech loans also went to CZs that had a higher prevalence of COVID-19 cases, and the effect is greater in the fintech sample of loans than when we use the full sample of PPP loans. Commuting zones where the number of COVID-19 cases per 10,000 people are one standard deviation greater received approximately 17% of a standard deviation more PPP loans. Making the same comparison between CZs with the full sample on loans, the number of PPP loans is only 5.1%-6% of a standard deviation greater. Places that were more affected during the early stages of the pandemic were able to get more aid in the form of PPP loans, especially from fintech lenders.

V. Conclusions

This paper's novel contribution is an empirical assessment of the PPP at the appropriate geographic scale to reflect a spatial comparison of loan disbursement against measures of regional banking concentration and labor market opportunity. In contrast to other work on these emergency business loans, we focus on commuting zones as the spatial unit of analysis, as well as leverage an oft-ignored measure of labor market opportunity, the employment/population ratio. We also inquire whether flows of loans indeed went to small businesses.

Our findings show that PPP loans went disproportionately towards more job-dense regions, effectively widening existing spatial labor market inequality. Furthermore, PPP loans flowed less towards those regions characterized by banking deserts, again reinforcing existing regional inequalities. Even when controlling for banking deserts, banking hinterlands also received fewer loans, highlighting the vulnerability of regional businesses to simple branch banking which appears to put such regions at a significant disadvantage relative to those featuring headquarters. The type of financial institution does matter for which commuting zones receive more PPP loans. Community banks, in particular, seem to be the most important type of lending institution for distributing these loans, which fits recent work on these institutions (e.g. Petach, Weiler, and Conroy 2021). For commuting zones which are relative banking deserts or hinterlands, fintech lenders are especially important as most of these loans were distributed to areas with fewer banks. The smallest businesses were systematically disadvantaged in loan distribution. Areas with greater non-white populations had no advantage in the first-round of loan distribution (as described by Howell, et al 2022), but finally gained more access to loans in the following disbursals.

This paper's findings suggest that the PPP distribution of resources seems to have furthered regional inequality both at the banking and labor market levels. Advantaged regions received more loans overall and even after the program was modified before the second-round of funding began these regions still received more loans. Running future programs like the PPP through existing banking structures will exacerbate existing inequalities, including banking deserts. A more targeted approach to the distribution of funds to places most affected by hardship would help lessen some of these underlying inequalities. The community banks result suggests that such banks' soft information and relationship lending is an important mechanism to more equitably spread loans. The findings on fintech lenders suggest that these institutions should be included in future policies as they help lessen the geographic inequalities that presently exist in banking.

Two more policy considerations emerge from this research. Specific targeting of loans to badly scarred regions would provide support where it is needed most. In a similar spirit, allocating funds by banks serving these particularly hard-hit communities would ensure that even the less nimble but possibly regionally important businesses would get an unhindered channel of funding access. Future work could link these loan/banking patterns to the rural/urban divide, as well as political leanings of the region in question. Overall, the findings on banking deserts and banking hinterlands underscore that when designing policies to be implemented locally through banks, the spatial distribution of such financial institutions should be considered to ensure that the policy is not creating or deepening spatial inequality – as was apparently the case for the PPP program.

Notes:

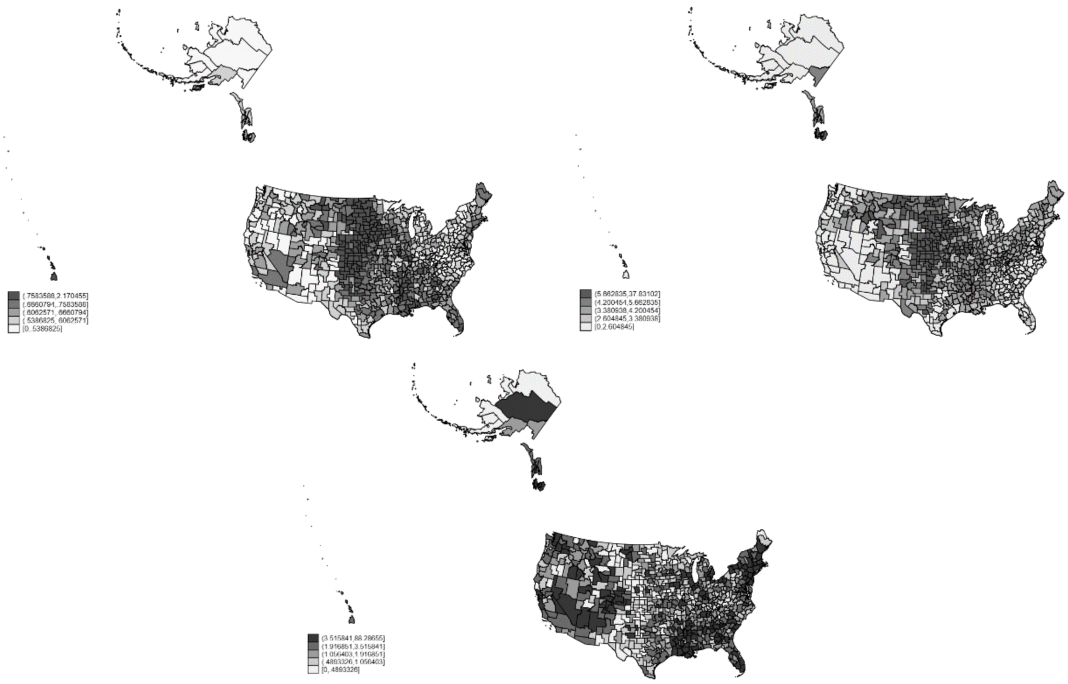
[1] We test an alternative aggregation procedure where zip codes are assigned to the county where the majority of businesses reside and do not find any substantial difference to our results.

Tables and Figures:

Table 1: Summary Statistics

	Mean	**Std. Dev.**	**Min.**	**Max.**	**N**
PPP Loans per Small Business	0.672	0.204	0	2.17	706
PPP Loan Amount per Small Business	51750.003	14474.729	0	131018.211	706
PPP Jobs Retained per Small Business	5.857	1.41	0	15.075	706
Round 1 Loans per Small Business	0.295	0.121	0	1.261	706
Round 1 Loan Amount per Small Business	36682.66	12374.749	0	97266.570	706
Round 1 Jobs Retained per Small Business	4.027	1.27	0	11.313	706
Banks + C.U.s per 10k people	4.492	2.908	0	37.831	706
Bank Headquarters per 10k people	0.636	0.972	0	9.653	706
COVID-19 Cases per 10k people	2.808	5.756	0	88.287	706
$\frac{Employment}{Population}$	0.403	0.065	0.224	0.666	706
$\frac{Median HH. Inc.}{Mean HH. Inc.}$	0.754	0.042	0.598	0.904	706
GDP per Capita in Thousands	54.045	25.504	22.774	392.175	706
Share of Pop. with at least a B.A.	0.236	0.078	0.073	0.556	706
Non-White Population Share	0.183	0.157	0.007	0.894	706
Small Businesses per 10k people	252.649	86.404	57.157	1005.714	706
Share of Small Businesses <10 Employees	0.748	0.05	0.607	1	706
Share of Small Businesses <50 Employees	0.962	0.017	0.911	1	706

Figure 1: Geographic Distribution of PPP Loans, Banks and COVID-19 Cases



Panel (a) on the upper left shows the geographic distribution of PPP loans per small business. Panel (b) on the upper right shows the geographic distribution of banks per 10,000 people. Panel (c) at the bottom shows the geographic distribution of COVID-19 cases per 10,000 people. All maps show the quintile distribution of the data.

Table 2: Total PPP Loan Program

	(1) PPP Loans per Small Business	(2) PPP Loan Amount per Small Business	(3) PPP Jobs Retained per Small Business
Banks + C.U.s per 10k people	1.002***	-0.165	-0.143
	(6.89)	(-1.29)	(-1.08)
(Banks + C.U.s per 10k people)²	-0.527***	0.007	-0.013
	(-5.76)	(0.08)	(-0.17)
Bank Headquarters per 10k people	0.333**	0.096	0.211
	(2.46)	(0.71)	(1.61)
(Bank HQs per 10k people)²	-0.115	-0.084	-0.099
	(-1.24)	(-0.51)	(-0.63)
COVID-19 Cases per 10k people	0.060**	0.066	0.031
	(2.32)	(1.26)	(0.61)
$\frac{Employment}{Population}$	0.203***	0.255***	0.217***
	(4.08)	(3.24)	(2.67)
$\frac{MedianHHInc.}{MeanHHInc}$	-0.009	0.005	-0.066
	(-0.22)	(0.10)	(-1.23)
GDP per Capita in Thousands	-0.124***	0.072	-0.091
	(-2.84)	(0.70)	(-1.25)
Share of Pop. with at least a B.A.	0.072**	0.085	-0.067
	(2.14)	(1.31)	(-1.00)
Non-White Population Share	0.159***	-0.018	-0.000
	(3.40)	(-0.27)	(-0.00)
Share of Sm. Businesses <10 Employees	-0.148***		
	(-3.39)		
PPP Loans		0.247***	0.142**
		(3.02)	(2.54)
Observations	706	706	706
R^2	0.570	0.224	0.061

Standardized coefficients reported. Robust standard errors were calculated. T-statistics in parentheses. Employment statistics are from April 2020. Small business data comes from the most recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

Table 3: First-Round of PPP Program

	(1) PPP Loans per Small Business	(2) PPP Loan Amount per Small Business	(3) PPP Jobs Retained per Small Business
Banks + C.U.s per 10k people	0.968***	0.021	0.051
	(7.05)	(0.18)	(0.42)
(Banks + C.U.s per 10k people)²	-0.564***	-0.109	-0.139*
	(-6.69)	(-1.55)	(-1.82)
Bank Headquarters per 10k people	0.397***	0.209*	0.364***
	(2.96)	(1.68)	(2.91)
(Bank HQs per 10k people)²	-0.272***	-0.258*	-0.338**
	(-3.39)	(-1.75)	(-2.15)
COVID-19 Cases per 10k people	-0.035*	0.006	-0.033
	(-1.80)	(0.13)	(-0.80)
$\frac{Employment}{Population}$	0.229***	0.318***	0.262***
	(5.45)	(4.38)	(3.72)
$\frac{MedianHHInc}{MeanHHInc}$	0.038	0.014	-0.046
	(0.93)	(0.28)	(-0.88)
GDP per Capita in Thousands	-0.147***	0.018	-0.127***
	(-4.56)	(0.24)	(-2.75)
Share of Pop. with at least a B.A.	-0.032	0.059	-0.034
	(-0.98)	(0.95)	(-0.56)
Non-White Population Share	0.050	-0.020	0.013
	(1.37)	(-0.34)	(0.22)
Share of Small Businesses <10 Employees	-0.155***		
	(-4.32)		
PPP Loans		0.070	-0.018
		(1.28)	(-0.57)
Observations	706	706	706
R^2	0.572	0.149	0.100

Standardized coefficients reported. Robust standard errors were calculated. T-statistics in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

Table 4: All PPP Loans per Small Business: Disaggregated Bank Types

	(1) Original Specification	(2) Banks & Credit Unions	(3) Community Banks & Credit Unions
Banks + C.U.s per 10k people	1.002***		
	(6.89)		
(Banks + C.U.s per 10k people)²	-0.527***		
	(-5.76)		
Banks per 10k people		1.030***	
		(6.57)	
(Banks per 10k people)²		-0.552***	
		(-5.93)	
Credit Unions per 10k people		-0.019	-0.049
		(-0.39)	(-1.02)
(Credit Unions per 10k people)²		0.044	0.049
		(0.97)	(1.12)
Community Banks per 10k people			1.171***
			(8.87)
(Community Banks per 10k people)²			-0.581***
			(-7.95)
Non-Community Banks per 10k people			0.367***
			(5.29)
(Non-Community Banks per 10k people)²			-0.247***
			(-3.57)
Bank Headquarters per 10k people	0.333**	0.305**	0.183
	(2.46)	(2.12)	(1.32)
(Bank Headquarters per 10k people)²	-0.115	-0.109	-0.026
	(-1.24)	(-1.14)	(-0.27)
Observations	706	706	706
R^2	0.570	0.576	0.606

Standardized coefficients reported. Full set of controls included from equation 1 but not reported. Robust standard errors were calculated. T-statistics in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

Table 5: First-Round PPP Loans per Small Business: Disaggregated Bank Types

	(1) Original Specification	(2) Banks & Credit Unions	(3) Community Banks & Credit Unions
Banks + C.U.s per 10k people	0.968***		
	(7.05)		
(Banks + C.U.s per 10k people)²	-0.564***		
	(-6.69)		
Banks per 10k people		0.947***	
		(6.32)	
(Banks per 10k people)²		-0.547***	
		(-6.07)	
Credit Unions per 10k people		0.147***	0.099*
		(2.69)	(1.78)
(Credit Unions per 10k people)²		-0.114*	-0.098
		(-1.77)	(-1.44)
Community Banks per 10k people			1.147***
			(7.60)
(Community Banks per 10k people)²			-0.621***
			(-7.12)
Non-Community Banks per 10k people			0.181***
			(2.81)
(Non-Community Banks per 10k people)²			-0.140***
			(-3.98)
Bank Headquarters per 10k people	0.397***	0.385***	0.146
	(2.96)	(2.70)	(1.01)
(Bank Headquarters per 10k people)²	-0.272***	-0.260***	-0.120
	(-3.39)	(-3.11)	(-1.46)
Observations	706	706	706
R^2	0.572	0.574	0.612

Standardized coefficients reported. Full set of controls included from equation 1 but not reported. Robust standard errors were calculated. T-statistics in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

Table 6: PPP Loans per Small Business: Second-Round Loans and Fintech Lenders

	(1) Round 2 Loans	(2) Fintech Loans
Banks + C.U.s per 10k people	0.700***	-0.634***
	(4.41)	(-5.92)
Bank Headquarters per 10k people	0.154	0.384***
	(1.07)	(3.71)
(Banks + C.U.s per 10k people)^2	-0.317**	0.221***
	(-2.47)	(4.61)
(Bank Headquarters per 10k people)^2	0.074	-0.059
	(0.59)	(-1.23)
COVID-19 Cases per 10k people	0.130***	-0.021
	(3.18)	(-0.32)
$\frac{Employment}{Population}$	0.103*	0.076
	(1.76)	(1.18)
$\frac{MedianHHInc.}{MeanHHInc.}$	-0.051	0.177***
	(-1.15)	(3.84)
GDP per Capita in Thousands	-0.062	0.012
	(-1.11)	(0.28)
Share of Pop. with at least a B.A.	0.150***	-0.158***
	(3.42)	(-4.23)
Non-White Population Share	0.204***	-0.013
	(4.04)	(-0.27)
Share of Small Businesses <10 Employees	-0.096*	0.210***
	(-1.88)	(4.95)
Observations	706	706
R^2	0.327	0.469

Standardized coefficients reported. Robust standard errors were calculated. T-statistics in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

A. Appendix

Table A1: Non- Standardized PPP Loans Per Small Business

	PPP Loans per Small Business	PPP Loans per Small Business
Banks + C.U.s per 10k people	0.0702***	0.0705***
	(0.0102)	(0.0105)
Banks + C.U.s per 10k people Squared	-0.00161***	-0.00159***
	(0.000280)	(0.000286)
Bank HQs per 10k people	0.0698**	0.0731**
	(0.0284)	(0.0291)
Bank HQs per 10k people Squared	-0.00417	-0.00504
	(0.00336)	(0.00361)
COVID-19 Cases per 10k people	0.00211**	0.00182**
	(0.000910)	(0.000870)
Employment/Population	0.639***	0.611***
	(0.157)	(0.163)
Median HH. Inc./Mean HH. Inc.	-0.0439	-0.0219
	(0.195)	(0.192)
GDP per Capita in Thousands	-0.000987***	-0.000950***
	(0.000347)	(0.000349)
Share of Pop. with at least a B.A.	0.188**	0.150*
	(0.0881)	(0.0853)
Non-White Population Share	0.207***	0.214***
	(0.0609)	(0.0594)
Share of Small Businesses <10 Employees	-0.600***	
	(0.177)	
Share of Small Businesses <50 Employees		-1.764***
		(0.493)
Constant	0.553**	1.800***
	(0.244)	(0.557)
Observations	706	706
R^2	0.570	0.570

Point estimates reported. Robust standard errors are in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

Table A2: Non-Standardized PPP Loan Amount and Jobs Retained per Small Business

	PPP Loan Amount per Small Business	PPP Jobs Retained per Small Business
Banks + C.U.s per 10k people	-808.05	-0.0875
	(644.4)	(0.0639)
Banks + C.U.s per 10k people Squared	10.48	0.000242
	(18.47)	(0.00166)
Bank Headquarter s per 10k people	1500.8	0.308
	(2049.9)	(0.191)
Bank HQs per 10k people Squared	-201.3	-0.0240
	(431.3)	(0.0397)
COVID-19 Cases per 10k people	229.2	0.0113
	(145.2)	(0.0131)
Employment/Population	57140.7***	4.727***
	(17869.7)	(1.768)
Median HH. Inc./Mean HH. Inc.	-8240.8	-2.775
	(16790.8)	(1.809)
GDP per Capita in Thousands	55.86	-0.00409
	(62.06)	(0.00421)
Share of Pop. with at least a B.A.	30043.2**	-0.368
	(12019.0)	(1.175)
Non-White Population Share	915.1	0.141
	(6049.8)	(0.681)
PPP Loans	0.1673	0.00001***
	(0. .0554)	(0.000003)
Constant	28154.5**	6.518***
	(13124.2)	(1.430)
Observations	706	706
R^2	0.179	0.046

Point estimates reported. Robust standard errors are in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

Table A3: Non-Standardized First-Round PPP Loans per Small Business

	Round 1 Loans per Small Business	Round 1 Loans per Small Business
Banks + C.U.s per 10k people	0.0401***	0.0389***
	(0.00568)	(0.00582)
Banks + C.U.s per 10k people Squared	-0.00102***	-0.000980***
	(0.000152)	(0.000155)
Bank Headquarters per 10k people	0.0492***	0.0512***
	(0.0166)	(0.0168)
Bank HQs per 10k people Squared	-0.00584***	-0.00647***
	(0.00172)	(0.00176)
COVID-19 Cases per 10k people	-0.000722*	-0.000897**
	(0.000400)	(0.000411)
Employment/Population	0.426***	0.418***
	(0.0782)	(0.0823)
Median HH. Inc./Mean HH. Inc.	0.111	0.113
	(0.118)	(0.118)
GDP per Capita in Thousands	-0.000692***	-0.000655***
	(0.000152)	(0.000149)
Share of Pop. with at least a B.A.	-0.0492	-0.0726
	(0.0504)	(0.0503)
Non-White Population Share	0.0385	0.0405
	(0.0281)	(0.0283)
Share of Small Businesses <10 Employees	-0.371***	
	(0.0860)	
Share of Small Businesses <50 Employees		-0.843***
		(0.253)
Constant	0.187	0.729**
	(0.134)	(0.291)
Observations	706	706
R^2	0.572	0.566

Point estimates reported. Robust standard errors are in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

Table A4: Non-Standardized First-Round Loan Amount and Jobs Retained per Small Business

	Round 1 Loan Amount per Small Business	Round 1 Jobs Retained per Small Business
Banks + C.U.s per 10k people	6.070	0.0246
	(498.9)	(0.0525)
Banks + C.U.s per 10k people Squared	-17.94	-0.00270*
	(12.98)	(0.00145)
Bank Headquarters per 10k people	2660.6*	0.473***
	(1581.3)	(0.162)
Bank HQs per 10k people Squared	-561.8*	-0.0763**
	(323.6)	(0.0354)
COVID-19 Cases per 10k people	29.44	-0.00760
	(101.5)	(0.00877)
Employment/Population	60700.8***	5.104***
	(13893.2)	(1.370)
Median HH. Inc./Mean HH. Inc.	1750.9	-1.318
	(14629.6)	(1.572)
GDP per Capita in Thousands	12.47	-0.00637***
	(36.33)	(0.00224)
Share of Pop. with at least a B.A.	12745.3	-0.638
	(9420.4)	(0.933)
Non-White Population Share	-926.4	0.0894
	(4475.7)	(0.480)
PPP Loans	0.0409	0.0000001
	(0.0318)	(0.000001)
Constant	6844.0	3.234***
	(11108.5)	(1.184)
Observations	706	706
R^2	0.145	0.100

Point estimates reported. Robust standard errors are in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

Table A5: Non-Standardized Sequential Addition of Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Banks + C.U.s per 10k people	0.0438***	0.0785***	0.0643***	0.0607***	0.0609***	0.0547***	0.0541***	0.0531***	0.0540***	0.0610***	0.0702***
	(0.00874)	(0.00531)	(0.00834)	(0.0100)	(0.00996)	(0.00980)	(0.00992)	(0.00998)	(0.01000)	(0.0108)	(0.0102)
(Banks + C.U.s per 10k people)^2		-0.00176***	-0.00144***	-0.00134***	-0.00133***	-0.00125***	-0.00123***	-0.00120***	-0.00121***	-0.00141***	-0.00161***
		(0.000206)	(0.000228)	(0.000280)	(0.000277)	(0.000284)	(0.000288)	(0.000296)	(0.000292)	(0.000298)	(0.000280)
Bank Headquarters per 10k people			0.0385**	0.0597**	0.0642**	0.0693**	0.0716**	0.0732**	0.0770***	0.0728**	0.0698**
			(0.0158)	(0.0281)	(0.0283)	(0.0277)	(0.0286)	(0.0286)	(0.0287)	(0.0292)	(0.0284)
(Bank Headquarters per 10k people)^2				-0.00349	-0.00394	-0.00518	-0.00563	-0.00575	-0.00599*	-0.00568	-0.00417
				(0.00329)	(0.00330)	(0.00334)	(0.00363)	(0.00371)	(0.00362)	(0.00364)	(0.00336)
COVID-19 Cases per 10k people					0.00330***	0.00292**	0.00259**	0.00277**	0.00237**	0.00184*	0.00211**
					(0.00113)	(0.00115)	(0.00112)	(0.00115)	(0.00114)	(0.00103)	(0.000910)
$\frac{Employment}{Population}$						0.529***	0.605***	0.667***	0.572***	0.675***	0.639***
						(0.118)	(0.118)	(0.128)	(0.152)	(0.171)	(0.157)
$\frac{MedianHHInc}{MeanHHInc}$							-0.283	-0.248	-0.207	-0.0992	-0.0439
							(0.202)	(0.192)	(0.192)	(0.202)	(0.195)
GDP per Capita in Thousands								-0.000591*	-0.000640*	-0.000853**	-0.000987***
								(0.000337)	(0.000332)	(0.000340)	(0.000347)
Share of Pop. with at least a B.A.									0.143	0.152	0.188**
									(0.0895)	(0.0941)	(0.0881)
Non-White Population Share										0.197***	0.207***
										(0.0684)	(0.0609)
Share of Small Businesses <10 Employees											-0.600***
											(0.177)
Constant	0.476***	0.370***	0.400***	0.405***	0.392***	0.204***	0.389**	0.371**	0.343**	0.171	0.553**
	(0.0369)	(0.0173)	(0.0227)	(0.0245)	(0.0242)	(0.0490)	(0.155)	(0.151)	(0.150)	(0.175)	(0.244)
Observations	706	706	706	706	706	706	706	706	706	706	706
R^2	0.390	0.477	0.495	0.497	0.506	0.529	0.532	0.537	0.539	0.556	0.570

Point estimates reported. Robust standard errors are in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

Table A6: PPP Loans per Small Business: Alternative Measure of Smallest Business Share

	(1) PPP Loans per Small Business	(2) Round 1 Loans per Small Business
Banks + C.U.s per 10k people	1.006***	0.940***
	(6.70)	(6.69)
(Banks + C.U.s per 10k people)²	-0.519***	-0.543***
	(-5.54)	(-6.32)
Bank Headquarters per 10k people	0.349**	0.414***
	(2.52)	(3.05)
(Bank HQs per 10k people)²	-0.139	-0.301***
	(-1.40)	(-3.68)
COVID-19 Cases per 10k people	0.051**	-0.043**
	(2.09)	(-2.18)
$\frac{Employment}{Population}$	0.194***	0.224***
	(3.76)	(5.07)
$\frac{MedianHHInc.}{MeadHHInc}$	-0.004	0.039
	(-0.11)	(0.96)
GDP per Capita in Thousands	-0.119***	-0.139***
	(-2.72)	(-4.40)
Share of Pop. with at least a B.A.	0.058*	-0.047
	(1.76)	(-1.44)
Non-White Population Share	0.164***	0.053
	(3.60)	(1.43)
Share of Small Businesses <50 Employees	-0.151***	-0.122***
	(-3.58)	(-3.33)
Observations	706	706
R^2	0.570	0.566

Standardized coefficients reported. Robust standard errors were calculated. T-statistics in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

Table A7: Second-Round of PPP Loans and Fintech Loans: Alternative Measure of Smallest Business Share

	(1) Round 2 Loans	(2) Fintech Loans
Banks + C.U.s per 10k people	0.734***	-0.530***
	(4.58)	(-5.41)
(Banks + C.U.s per 10k people)²	-0.325**	0.233***
	(-2.54)	(5.39)
Bank Headquarters per 10k people	0.164	0.343***
	(1.12)	(3.50)
(Bank Headquarters per 10k people)²	0.062	-0.173***
	(0.48)	(-4.30)
$\frac{MedianHHInc}{MeanHHInc}$	-0.044	0.174***
	(-1.01)	(4.05)
$\frac{Employment}{Population}$	0.093	0.080
	(1.57)	(1.21)
GDP per Capita in Thousands	-0.062	-0.007
	(-1.10)	(-0.17)
Share of Pop. with at least a B.A.	0.140***	-0.145***
	(3.30)	(-3.96)
Non-White Population Share	0.211***	-0.020
	(4.33)	(-0.41)
Share of Small Businesses <50 Employees	-0.133***	0.203***
	(-2.83)	(5.07)
Observations	706	706
R^2	0.332	0.485

Standardized coefficients reported. Robust standard errors were calculated. T-statistics in parentheses. Employment statistics are from April 2020. Small business data comes from themost recent County Business Patterns (2019). p<0.1* p<0.05** p<0.01***

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