The Cost of Banking Deserts: Racial Disparities in Access to PPP Lenders and their Implications

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Abstract

Many government support programs for small businesses are designed to pass through banks and credit unions. However, this poses barriers for minority communities that are less connected to financial institutions for obtaining this support. Using the latest program for supporting small businesses, the Paycheck Protection Program (PPP), as an example, we show that there was a large disparity in both the presence and density of PPP enrolled lenders by racial composition of the neighborhood. This difference is both due to a lower number of lenders in those neighborhoods in general, and by the fact that the lenders that do operate there are small credit unions without a previous relationship with the Small Business Administration. More heavily Black neighborhoods have significantly lower take-up of PPP loans, particularly in lower population (more rural) areas where this disparity is most salient. Through an instrumental variables analysis, we show that the intensive margin of access to enrolled lenders can explain about 32% of the racial disparity in take up within the relevant areas. Our results suggest that government programs that provide "support through banks" can have undesirable distributional implications.

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1 Introduction

Many government lending programs for small businesses, such as the Small Business Administration (SBA) 7a and 504 programs, are primarily intermediated by banks and credit unions. The main avenue of government support for small businesses during the Covid-19 crisis, the Payment Protection Program (PPP), was also designed to be intermediated by third party lenders who are tasked for taking in loan applications and loan forgiveness applications.[1] This channel of support has its advantages: banking institutions may have better connections with their local communities and more resources to quickly distribute funds than government agencies, which explains the widespread use of third party lenders as distributors of government support.

Nevertheless, we show that over-reliance on established financial institutions can have undesirable distributional implications. In particular, it leaves behind minority communities which have less access to these financial institutions. Taking the PPP program as an example, we show that Zip codes with a greater proportion of Black population have worse access to enrolled lenders. A 10 percentage point increase in the share of Black population in a Zip code correlates with a 1.0% decrease in the likelihood of having any enrolled lender in their Zip code, and, conditional on having at least one, a 4.1% decrease in the number of branches of enrolled lenders in their Zip code. This is both because there are fewer lenders in Black neighborhoods in general, and because the lenders that *are* there are more likely to be small credit unions with no previous relationships with the SBA and are less likely to enroll in the program.

These differences in geographical access to financial institutions, which we find to be particularly severe in lower population (more rural) areas, correlate with the lower take-up of PPP loans in those areas. Furthermore, borrowers in Black neighborhoods that do receive the government support tend to use Fintech lenders and travel further. Therefore, our descriptive results suggest that the unequal distribution of financial institutions across geographical access may be a driver of differential pass-through of government support. As an analogy to food deserts, which are well-defined geographical areas with limited access to healthy and affordable foods[2], we study the disparate distribution of financial institutions in the form of "government support banking deserts," which we characterize as geographical areas with limited access to financial institutions that have sufficient scale and experience to

[1]PPP loans are structured as loans but are forgivable if the business used at least 60% of the loan for eligible payroll costs over a span of 24 weeks, among other conditions. Therefore, it is more akin to a grant for maintaining employment than a traditional loan.

[2]Food deserts are defined by the USDA: https://www.ers.usda.gov/data-products/food-access-research-atlas/documentation/. Academic studies of food deserts include Walker, Keane, and Burke (2010) and Allcott, Diamond, Dubé, Handbury, Rahkovsky, and Schnell (2019).

intermediate government support programs for small businesses.

To assess the causal effect of the presence of financial institutions in a neighborhood, we use an instrumental variables approach. More specifically, we use the failure of small community banks, which tend to be acquired by neighboring larger banks, to instrument for the entry of a larger bank which is more likely to enroll in the PPP program. We find that neighborhoods where their community bank failed, all else equal, ended up with more enrolled lenders and higher take-up of PPP loans. The failures of commercial banks in the US are primarily driven by exposure to commercial real estate loans as well as residential mortgage backed securities (RMBS), and not small business loans, as examined in Antoniades (2020). More importantly for the validity of our estimates, to the extent that community bank failures are correlated with an unobserved deterioration of local economic conditions, it would only make our estimates more conservative since areas with worse economic conditions have lower take-up of PPP because businesses in those areas tend to close altogether. We find that Zip codes exposed to past local bank failures have more enrolled branches, with a 10% increase in the number of enrolled branches in a Zip code corresponding to a 1.2% increase in the take-up of PPP loans. Our IV analysis shows that access to financial institutions explains 32% of the difference in PPP take-up among the lower population (more rural) areas.

To be clear, we view the causal effect of geographical proximity to enrolled financial institutions on PPP take-up as capturing more than the physical costs of travelling further to reach an enrolled lender, much like how standard models of trade costs captures more than physical transportation costs.[3] In particular, enrolled financial institutions tend to engage in advertising and promotion of the PPP program both among their existing small business clients and more broadly, which may increase awareness and decrease misconceptions about the program's requirements. Information frictions are an important driver of PPP take-up among small businesses, as shown in Humphries, Neilson, and Ulyssea (2020). The impact of the banking deserts we study, then, may be due to the alleviation of information frictions in addition to the physical costs of access.[4]

Our paper is related to the literature on the unequal access to bank branches and banking deserts. Earlier studies have documented the existence of areas with few to no bank branches which are more concentrated in poorer areas, though the correlation between minority presence and banking deserts depends on the definition of "minority" used. In particular, Morgan, Pinkovskiy, and Yang (2016) finds that banking deserts are negatively correlated with

[3]For example, social connectedness has been found to be an important explanation for trade costs increasing with distance, as shown in Bailey, Gupta, Hillenbrand, Kuchler, Richmond, and Stroebel (2020).

[4]We are in the process of fielding a small business survey to get at the mechanisms more precisely. A preliminary draft of our survey can be found in Appendix B.

income but are less prominent in majority-minority areas, whereas Kashian, Tao, and Drago (2018) finds that African Americans are more likely to live in banking deserts, a result corroborated by more geographically isolated studies including Hegerty (2016) and Miller (2015). We contribute to this literature by showing that the disparity in access to lenders is increased if we expand the definition of "banking deserts" to count only lenders that enroll in government support programs for small businesses. In other words, not only do African American neighborhoods have fewer banks and credit unions, the banks and credit unions that do operate there are less likely to be able and willing to serve as an intermediary for government programs for small businesses. In addition, we demonstrate a tangible consequence of unequal access, in the form of lower take-up of government support.

We also contribute to the literature on PPP loans. Granja, Makridis, Yannelis, and Zwick (2020) finds that, due to selective decisions by large lenders on where to approve Round 1 PPP loans, Round 1 PPP loans flowed to areas that are less hit by the crisis. We look at disparities in geographical access to banking rather than selective intermediation by large banks, and focus on PPP enrollment by the end of Round 2 when the problem of selective intermediation is less severe.[5] More importantly, we focus on how differences in the presence of enrolled lenders in a neighborhood cause disparities in access by race, which is a problem distinct from that of larger lenders selectively choosing which business' application to process first. We also use an instrumental variables approach to to assess the causal effects of enrolled branches on take-up. Howell, Kuchler, and Stroebel (2021) examines the types of lenders used by minority-owned businesses, though not geographical differences in access or their implications.

The literature finds mixed effects of PPP takeup on employment, depending on the types of business examined. Granja et al. (2020) and Chetty, Friedman, Hendren, Stepner, and Team (2020) find that the effect of PPP loans on employment is small in aggregate. On the other hand, Bartik, Cullen, Glaeser, Luca, Stanton, and Sunderam (2020c) shows that PPP loans did have a large employment effect for a sample of smaller businesses. Since the businesses in the rural, minority areas where the disparities we identify are largest are more likely to be small, our results may have employment implications.

Finally, our paper contributes to the broader literature on business behavior during Covid-19. Bartik, Bertrand, Cullen, Glaeser, Luca, and Stanton (2020a) finds that many

[5] Indeed, journalists have reported that PPP take-up by Black congressional districts was lower in Round 1 but entirely caught up by the end of Round 2, suggesting that selective intermediation by large banks may be a temporary problem: https://www.bloomberg.com/graphics/2020-ppp-racial-disparity/. The reason we find a persistent racial disparity in take-up at the end of Round 2 is by looking at lower population areas where differences in geographical access to enrolled banks is the greatest, and by conducting analyses at the Zip code level which more closely approximates racial distributions of neighborhoods.

small businesses are financially fragile, and many businesses (about 43%) temporarily closed during the crisis. Wang, Yang, Iverson, and Kluender (2021) finds that bankruptcy takeup is lower during Covid-19 than earlier downturns. In terms of re-opening, Balla-Elliott, Cullen, Glaeser, Luca, and Stanton (2020) finds that Covid-19 demand expectations explain a large part of re-opening decisions. Bartik, Cullen, Glaeser, Luca, and Stanton (2020b) finds that better educated and higher paid industries are more likely to switch to remote work.

The rest of this paper is organized as follows. Section 2 describes our data and summary statistics. Section 3 shows our reduced-form descriptive results on the geographical distribution of enrolled lenders and its correlation with the racial composition of neighborhoods. Section 4 presents our instrumental variables results. Section 5 concludes.

2 Data

We use the Federal Deposit Insurance Corporation's Summary of Deposits (SOD) data to get information on the branch locations of banks and the National Credit Union Administration (NCUA)'s Credit Union and Corporate Call Report Data to get information on the branch locations of credit unions. We merge data on financial institutions with PPP data through August 08, 2020 and data from the 7(a) and 502 loan programs released by the SBA.[6] The data includes information about the names and Zip codes of the businesses that took out the loans as well as the names of the financial institutions. We use a fuzzy matching procedure to match the names of the financial institutions in the PPP data with the corresponding entities in the SOD and NCUA Call report data, using state as tie-breakers. Furthermore, we identify FinTech lenders using a list adapted from Howell, Kuchler, and Stroebel (2021) which we display in Appendix Table A1.

We then combine the data on PPP loans with Zip code Business Patterns (ZBP) data in 2018 from the US Census Bureau to compute the take-up rate of PPP loans by Zip code. The ZBP includes data on the size distribution of businesses on a Zip code level. Take-up rate is calculated for each Zip code i using the following equation[7]:

$$\text{PPP Take-up Rate}_i = \frac{\text{\# of PPP loans}_i}{\text{\# of small businesses}_i}. \tag{1}$$

To make the data comparable, we take the following approaches. First, since the ZBP excludes businesses from certain industries as well as self-employed individuals, we remove

[6] We used the March 2, 2021 version of the SBA PPP data in this paper.

[7] For a small number of Zip codes, we calculate a take-up rate greater than one. This most likely arises from 2018 ZBP data being outdated compared to the PPP data, which concerns small businesses in 2020. We set the take-up rate of these Zip codes to one.

PPP loan records for businesses with corresponding features.[8] Second, we calculate the zip-level number of small businesses as the number of businesses in each Zip code with less than 500 employees[9]. In addition to the take-up rate, we also use the ZBP to calculate average employment size of small businesses and share of businesses in each NAICS-2 industry, both on a Zip code level.

We obtain Zip-level demographic and geographical information from various data sources. Racial composition is based on 5-year estimates of the American Community Survey (ACS) from 2014 to 2018 on a census tract level, which we then collapse to a Zip code level using a crosswalk file provided by the Office of Policy Development and Research of U.S. Department of Housing and Urban Development (HUD).[10] Population density for Zip codes is calculated using the 2010 Decennial Census and 2013 U.S. Gazetteer files. Distance between Zip codes is provided by the NBER Zip Code Distance Database. Commuting zones are defined over counties and cover the entire US, and we obtain their definitions and their population from the US Department of Agriculture Economics Research Service. Furthermore, we separate commuting zone populations into three categories:

$$CZ\_cat = \begin{cases} 1 \text{ , if commuting zone population} & \leq 515,013, \\ 2 \text{ , if commuting zone population} & > 515,013 \text{ and } \leq 1,604,457, \\ 3 \text{ , if commuting zone population} & > 1,604,457, \end{cases} \tag{2}$$

where the cut-offs correspond to the 50th and 75th percentiles of commuting zone population by Zip code. We picked this cut-off because more than half of US Zip codes are rural,[11] such that a Zip code in an area with a lower population are more rural and more "remote" in the sense of having less people within their commuting area. As an example, Williamstown, MA, a college town located in a rural area, has a Zip code with CZ_cat =

[8] Specifically, we exclude PPP loans taken by business in the following sectors: crop and animal production (NAICS 111,112), rail transportation (NAICS 482), Postal Service (NAICS 491), pension, health, welfare, and vacation funds (NAICS 525110, 525120, 525190), trusts, estates, and agency accounts (NAICS 525920), office of notaries (NAICS 541120), private households (NAICS 814), and public administration (NAICS 92). We also exclude loans taken by businesses classified as "Self-employed Individuals".

[9] According to the eligibility conditions for PPP loans, posted on the SBA website `www.sba.gov/funding-programs/loans/coronavirus-relief-options/paycheck-protection-program`, small businesses can apply if their have less than 500 employees, or if they meet the SBA industry size standard if more than 500. Since the size standard varies across industries defined at a detailed level, our measure might underestimate the number of small businesses. We correct this bias by controlling for 2-digit NAICS industry shares of small businesses in each Zip code in our analysis.

[10] We focus our analysis at the zip code level because the welfare of businesses in minority neighborhoods may be more relevant to minorities than the owners' race per se. We also conduct a robustness check of our lender type results using the owners' race identified from their names using the algorithm of Ambrose, Conklin, and Lopez (2020).

[11] Source: http://proximityone.com/zip_urban_rural.htm

1. Amherst, MA, which is also in a small college town but is in the more populated Five Colleges area, is located in a Zip code with CZ_cat = 2. Cambridge, MA has a CZ_cat = 3.

Finally, we use the Federal Deposit Insurance Corporation (FDIC)'s Failed Bank List to construct our instrument. We take the entire list of bank failures before 2020, which includes the period from October 1, 2000 to December 31, 2019. We then restrict the sample to small banks that have less than or equal to 10 branches before they failed, which are banks that are less to have a relationship with SBA and are less likely to enroll in the PPP program. The historical failure of these small local banks, conditioned on the 2000 number of small bank branches, are correlated more enrolled branches and more take-up of PPP loans in the Zip code and uncorrelated with the unemployment claim rate in February 2020. Summary statistics for our variables are shown in Table 1.

3 Descriptive Analysis

3.1 Access to lenders

As a first step, we investigate if there is differential access to financial institutions associated with racial composition of Zip codes. The primary specification is

$$Y_{ic} = \alpha + \beta \text{Black Ratio}_i + \mathbf{X}_i \delta + \gamma_c + \varepsilon_{ic} \tag{3}$$

where Y_{ic} is the outcome variable of Zip code i in country c; Black Ratio$_i$ is the share of Black population in Zip code i; $\mathbf{X}_i$ is a vector of Zip code characteristics; and γ_c is a county-level fixed effect. For the outcome variable Y_{ic}, we use a dummy variable of whether the Zip code contains any lender, as well as log of the number of branches (of any lender). We thus examine racial disparity in both extensive and intensive margins of access to financial institutions. To control for other factors correlated with racial composition that might affect access (e.g. industrial composition and size), we include the following Zip code-level variables in the control vector $\mathbf{X}_i$: log number of establishments and squared, log population and squared, population density, and share of small businesses within each 2-digit NAICS industry. Standard errors are clustered on the Commuting Zone level.

In addition, we also examine heterogeneity in racial disparity across neighborhoods in commuting zones with different populations. As described earlier, we categorize Zip codes into three groups by the population of the respective commuting zones they are located in. "Low population" areas are Zip codes with a total 2010 population of under 515,013 in their commuting zone, representing 50% of all Zip codes. "Medium population" areas are Zip codes with a total population between 515,014 and 1,604,456 in their commuting zone, representing 25% of all Zip codes. Finally, "high population" areas are Zip codes with a population over 1,604,457 in their commuting zone, representing 25% of all Zip codes. For simplicity, these three areas are denoted as CZ group 1, 2, and 3, or "Low population CZ", "Medium population CZ", and "High population CZ", respectively. We separately estimate the racial gap in access for these three areas by interacting the coefficient on Black Ratio with dummies for the different areas in the following specification:

$$Y_{ic} = \alpha + \sum_k \beta_k \{\text{CZ group} = k\}_i \times \text{Black Ratio}_i + \mathbf{X}_i \delta + \gamma_c + \varepsilon_{ic} \tag{4}$$

where $\{\text{CZ group} = k\}_i$ is equal to one if Zip code i is located in one of the group k commuting zones.

Results under Equation (3) and Equation (4) are shown in Table 2. Column (1) shows that Zip codes with a 10% higher proportion of Black population is 0.77% less likely to contain any lender. Column (3) repeats the analysis in (1) using log(number of lenders within Zip code) as the dependent variable, conditional on the number of lenders being greater than zero, and shows that the gap is even wider in the intensive margin: a 10% higher Black population share is associated with a 2.1% lower number of branches, conditional on the Zip code having at least one lender. Decomposing across Zip codes by population of their commuting zones in Column (2) demonstrates that this racial disparity in access is statistically significant for Zip codes in both low density and medium density commuting zones, and is the strongest for low density areas. The racial gap in the intensive margin is statistically significant for all three CZ groups, as shown in Column (4) with the most significant gap being in the high density commuting zones.

To confirm that racial disparity in access is relevant in the context of PPP, Table 3 investigates whether Black Zip codes have worse access specifically to lenders that are enrolled in the PPP program. Columns (1) and (3) show that the difference in access is larger (more negative) in magnitude than before, suggesting that Black Zip codes have a even more pronounced disadvantage in access to PPP lenders rather than lenders in general. Decomposing the racial gap across areas with different population densities in columns (2) and (4) shows that the disparity in access to enrolled lenders are greater for the lower population commuting zones (CZ_cat=1) in both extensive and intensive margins.

Comparing coefficients between Table 2 and 3 shows that the racial disparity is worse when focusing on access to lenders enrolled in the PPP program rather than lenders in general. This indicates that the *kind* of lenders in the area matters in addition to the presence of *any* lender. By construction, it must be that lenders in more heavily Black neighborhoods are less likely to enroll. Indeed, Figure 1, which is a bin-scatter plot with the percent of Black residents in a Zip code on the x-axis and the fraction of bank and credit union branches that enrolled in PPP in a Zip code on the y-axis, shows that the fraction of lenders branches enrolled in PPP in a Zip code is negatively correlated with its percent of Black residents.

To verify that the relationship between the percent of residents that are Black and the probability of lender enrollment holds after we include county fixed effects and our control variables, we run branch level regressions of enrollment on lender and Zip code level controls with standard errors clustered by lender and county and results shown in Table 4. Column (1) of Table 4 shows that lender enrollment is decreasing in the percent of Black residents in a Zip code. Column (2) shows that the coefficient relationship between enrollment and the percent of Black residents is slightly stronger in the lower density commuting zones (CZ_cat=1 and CZ_cat=2). Finally, Column (3) of Table 4 shows that the relationship between lender enrollment and the Black ratio is mostly explained by three additional variables and their interactions: (i) a dummy variable for whether the lender is a credit union, (ii) a dummy variable for whether the lender is small (less than 10 branches), and (iii) a dummy variable for whether the lender is enrolled in either SBA 7(a) or 504 programs. While a small racial disparity remains, these three variables reduces the coefficient of black_ratio on enrollment by around three-quarters.

Table 5 examines the type of lenders that are more likely to be present in Black zip codes. Lenders in those zip codes are more likely to be credit unions, small, and less likely to have previous experience with SBA programs. Further examination through interactions of these variables in Columns (4) and (6) shows that the small lender result is primarily confined to credit unions: while credit unions operating in more heavily Black zip codes are smaller, the bank lenders tend to be larger. Furthermore, Column (5) and (7) shows that the credit unions operating in more Black zip codes are equally likely to enroll in SBA programs as otherwise, and banks that operate in more heavily Black zip codes do have more experience with the SBA. Therefore, the disparity in access is mainly driven by the fact that lenders in Black zip codes are more likely to be small credit unions, who may be less likely to have previous SBA experience because of their scale.

3.2 PPP take-up by racial composition of establishment neighborhood

Given the suggestive evidence that more heavily Black neighborhoods have worse access to lenders in general as well as PPP lenders in particular, we then examine if this racial gap translates to a racial disparity in access to support through the PPP program. As a first step, the bin scatter plot in Figure 2 shows a clearly negative correlation between PPP take-up rate and the share of Black population on a Zip code level. To perform a more careful descriptive analysis, we again invoke the specifications in equations (3) and (4), this time using take-up rate as the dependent variable. Our regressions thus estimate the neighborhood-level relationship between the share of Black population and the fraction of eligible businesses that end up receiving support through PPP.

Table 6 displays our results on the PPP take-up by racial composition of the establishment neighborhoods. In columns (1) and (2), we first look at the correlation between share of Black population and take-up rate without including any of the control variables. We find that on average, Zip codes with a 10% higher proportion of Black population have a 1.3% lower take-up rate of PPP loans. Separating this effect across Commuting Zones with different population densities in column (2) shows that the racial disparity is almost entirely restricted to the low population and medium population Commuting Zones. Controlling for neighborhood-level characteristics in columns (3) and (4) makes the coefficients somewhat smaller in magnitude, but does not take away statistical significance. To put our estimates in perspective, a small business in a Zip code with 100% Black population would be 8.4% less likely to obtain a PPP loan than its counterpart in a Zip code with no Black population, and 25.0% less likely than its counterpart if it is located in a low population Commuting Zone.

To summarize, controlling for county fixed effects and local characteristics, we find that small businesses Zip codes with a larger share of Black population are less likely to take up PPP loans. This effect is the most severe within low-density Commuting Zones, and also statistically significant within medium-density Commuting Zones. These results suggest that racial disparity in pass-through of government support does exist, and the relatively more rural areas suffer in particular.

3.3 Type of PPP Lender Used

In Section 3.1, we provided evidence that Black neighborhoods have fewer lenders in their Zip codes, and this applies to both lenders in general and lenders enrolled in the PPP program. However, one might still wonder if this necessarily implies racial disparity in access overall. For example, if a Black neighborhood has a comparable number of PPP lenders in *nearby* Zip codes, then it could have similar levels access to lenders despite the lack of financial institutions within the neighborhood itself.

To verify if the racial gap in access extends beyond the neighborhood level, we look at the type of lenders that PPP borrowers use and how they differ by zip codes. First, we define a set of lenders as "FinTech", based in part on a list from Howell, Kuchler, and Stroebel (2021) and listed in our Appendix Table A1. Second, we estimate the distance of each business to its lender by computing the distance between Zip code of the business and Zip code of the closest branch of the lender. Based on this distance measure, we define a loan as "remote" if the business is more than 100 miles away from the lender. Small businesses get their loans from a remote lender may have applied through online platforms or a remote application process. Third, we examine the distance between the small business and their lender PPP lender, conditional on it being non-FinTech and non-remote.

Figure 3 shows the correlation between distance to PPP lender and the proportion of Black population on a Zip code level through two bin scatter plots. Panel (a) shows that businesses in Zip codes with a higher Black population are significantly more likely to apply for PPP through a FinTech lender. Panel (b) shows that, conditional on non-FinTech lenders, Zip codes with a higher Black share have a higher share of "remote" PPP loans on average. Panel (c) shows that, even if we only inspect the non-FinTech and non-remote loans, businesses in Zip codes with a higher ratio of Black population obtain loans from lenders that are further away. These results indicate that the disparity in access to PPP lenders is correlated with higher usage of FinTech and further away options.

To more systematically analyze the relationship between racial composition and remoteness of PPP loans, we conduct loan-level regressions using the following specifications:

$$Y_{biz} = \alpha + \beta \text{Black Ratio}_i + \mathbf{X}_i \delta + \gamma_c + \varepsilon_{biz} \tag{5}$$

$$Y_{biz} = \alpha + \sum_k \beta_k \{\text{CZ group} = k\}_i \times \text{Black Ratio}_i + \mathbf{X}_i \delta + \gamma_z + \varepsilon_{biz} \tag{6}$$

where Y_{biz} is the outcome variable for a loan taken by business b in Zip code i and county z; γ_c are county fixed effects. Like before, we control for a vector of Zip code-level characteristics $\mathbf{X}_i$, and interact the coefficient on Black Ratio with dummies for different Commuting Zone population groups to investigate heterogeneity in the racial gap. For the outcome variable, we use a dummy variable equal to one if the PPP lender is remote, as well as log distance of business to its lender.

Results for regressions in equations 5 and 6 are shown in Table 7. Column (1) shows that a 10% higher ratio of Black population in the Zip code in which a business is located is associated with a 1.6 percentage point increase in the likelihood of the lender to be FinTech. Column (2) shows that within all Commuting Zone groups, businesses in Black Zip codes are more likely to acquire PPP loans from a FinTech lender, with the difference being highest among the high density Commuting Zones. Column (3) and (4) show that businesses in Zip codes with a higher share of Black population are also more likely to get their PPP loan from a remote lender, although the magnitude of the difference is lower than it is for FinTech and is concentrated among the high population commuting zones. As we turn to the intensive margin of distance, Column (5) reveals that business in Black Zip codes travel further overall to obtain PPP loans: businesses in a Zip code with a 10% higher Black ratio are on average 2.4% further away from their lenders. Column (6) confirms that this racial disparity is statistically significant regardless of population density of the Commuting Zone, and is the highest among the lower population commuting zones[12]. Our FinTech and distance results suggest that FinTech penetration may be more successful at making up for the racial disparities in PPP access in more urban, higher population areas, whereas businesses from minority Zip Codes in more rural areas still travelled further to get a loan from a brick and mortar lender.

4 Instrumental Variables estimates

Given the descriptive evidence in Section 3, which suggests that more heavily Black Zip codes have (1) worse access to lenders in general and particularly PPP lenders and (2) take up PPP loans at a lower rate, we now attempt to establish a connection between access to lenders and pass-through of PPP support, and examine how this connection can explain the racial disparity in take-up. Ideally, we would like to run the following regressions:

$$\text{Takeup}_{iz} = \alpha^1 + \sum_k \gamma_k^1 \{\text{CZ group} = k\}_i \times \text{Enrollment}_i + \sum_k \beta_k^1 \{\text{CZ group} = k\}_i \times \text{Black Ratio}_i + \mathbf{X}_i \delta^1 + \gamma_c^1 + \varepsilon_{iz} \tag{7}$$

$$\text{Takeup}_{iz} = \alpha^0 + \sum_k \beta_k^0 \{\text{CZ group} = k\}_i \times \text{Black Ratio}_i + \mathbf{X}_i \delta^0 + \gamma_c^0 + \varepsilon_{iz} \tag{8}$$

In equation (7), we regress PPP take-up rate of Zip code i in Commuting Zone z on a Zip-code level enrollment variable as well as the ratio of Black population, allowing for different coefficients across Commuting Zones with different population densities. For the enrollment variable, we use indicators on both extensive and intensive margins, i.e. a dummy variable for whether the Zip code contains a PPP-enrolled lender, and log of the number of PPP-enrolled lenders. The estimated coefficient $\hat{\beta}_k^1$ measures the relationship between enrollment of local lenders in the PPP program and take-up of PPP loans for each CZ group k. Moreover, by comparing the estimated coefficients on Black Ratio across Equation (7) and Equation (8),

[12]We also ran this analysis using name-assigned race of the business owner, with results in Table A2. Our FinTech and Remote results are broadly consistent. The distance results in Columns (5) and (6) are less significant. For Columns (5) and (6) of Tables 7 and A2, we also tried an alternative transformation of distance using the inverse hyperbolic sine function (IHS), first proposed by Burbidge, Magee, and Robb (1988), and the results are highly similar in terms of magnitude with the same level of statistical significance.

$\hat{\beta}_k^1$ and $\hat{\beta}_k^0$, we can also gauge the extent to which local access can explain racial disparity in the pass-through of PPP support.

However, the specification in Equation 7 is prone to endogeneity, since PPP enrollment is likely correlated with other local factors contained in the error term ε_{iz} that might affect PPP take-up. For example, better local economic conditions would prompt banks in general (including PPP-enrolled ones) to establish more branches in the corresponding Zip codes, and simultaneously lead to higher PPP take-up rate since local businesses are more resilient to the Covid shock and less likely to shut down. This would generate an upward bias in our estimate of the association between enrollment and take-up, $\hat{\gamma}_k^1$.

Therefore, to assess the causal effect of local access to PPP-enrolled lenders on take-up, we use the failure of small community banks, defined as banks with fewer than 10 branches, to proxy for PPP enrollment of local banks. Specifically, we define a dummy variable that is equal to 1 if the Zip code contains at least one branch of a failed bank. The rationale for choosing this instrument is that failed branches tend to be acquired by larger financial institutions, which are more likely to enroll in the PPP compared to small lenders. As a result, Zip codes with branches of failed banks should have more PPP-enrolled lenders relative to those without, after controlling for other local characteristics.

Regarding external validity of the instrument, Antoniades (2020) has shown that the failure of commercial banks in the US is primarily driven by exposure to commercial real estate loans as well as residential mortgage backed securities (RMBS), and not small business loans. In other words, bank failures may be mainly driven by shocks uncorrelated with local conditions of small businesses that would affect take-up of PPP loans. Moreover, even if some bank failures are indeed driven by deteriorating local economic conditions and thus violate the exclusion restriction, that would only make our IV estimate more conservative: businesses in areas with worse economic conditions are more likely to close down during the pandemic, and thus should be *less* likely to take-up PPP loans, rather than being more likely as we find. In line with this argument, Table A4 in the Appendix shows that Zip codes with branches of failed banks have a similar claim rate for unemployment insurance (UI) prior to Covid-19, in February 2020, with the point estimate for the difference being 0.265% and not statistically significant. Furthermore, Zip codes with higher UI claim rate in February are strongly correlated with a lower PPP take-up rate. Therefore, if anything, using this instrument may generate a downward bias on our estimated impact of access on PPP take-up.

Using the proposed instrument, we supplement the main regression in Equation 7 with a first-stage regression:

$$\text{Enrollment}_{ic} = \kappa + \rho\{\text{Has Failed Branch}\}_i + \mathbf{X}_i\mu + \varphi_c + \xi_{ic} \tag{9}$$

where Enrollment_{ic} is an enrollment variable of Zip code i in county c, and $\{\text{Has Failed Branch}\}_i$ is a dummy variable equal to one if Zip code i contains at least one failed bank branch.

Results for the first stage IV regression are shown in Table A3. As previously discussed, for the enrollment variable, we use both a dummy variable for whether a Zip code contains any PPP-enrolled lender, and log number of PPP-enrolled lenders a Zip code. The results indicate that our instrument is mostly relevant in the intensive margin. More specifically, Column (1) indicates that neighborhoods with branches of failed banks are about equally likely to have an enrolled lender as neighborhoods without failed banks. One possible explanation for this is that Zip codes with failed banks *and* no PPP-enrolled banks ex-ante is a small sample, and may be simply economically unattractive for big banks to enter through acquisitions. In contrast, Column (2) shows that, conditional on a Zip code containing at least one PPP-enrolled lender, Zip codes with at least one failed bank branch have a 9.1% higher number of enrolled lenders. This confirms the internal validity of our instrument for the intensive margin of access to PPP lenders.

For the second stage of the IV regression, we first run simpler specifications that isolate the impact of local access to enrolled lenders on PPP take-up:

$$\text{Takeup}_{ic} = \alpha + \gamma\text{Enrollment}_i + \mathbf{X}_i\delta^1 + \gamma_c + \varepsilon_{ic} \tag{10}$$

$$\text{Takeup}_{ic} = \alpha + \sum_k \gamma_k\{\text{CZ group} = k\}_i \times \text{Enrollment}_i + \mathbf{X}_i\delta + \gamma_c + \varepsilon_{ic} \tag{11}$$

Results for Equation (10) and Equation (11) are shown in Table 9. Column (1) shows that doubling the number of PPP-enrolled lenders in a Zip code would lead to an increase of 11.9 percentage points in the take-up rate of PPP loans. Column (2) examines this effect separately for areas with different population densities, and finds the magnitude to vary between 11.8 and 12.6 percentage points. These results show that local access to particular lenders does matter for actual pass-through of government support through PPP loans.

Finally, we run the regressions in Equation 7 and Equation 8 to examine the explanatory power of the intensive margin access to PPP lenders for racial disparity in PPP take-up. For the second stage regression in Equation 7, we instrument for enrollment using our bank failure IV. Table 10 displays the results. Column (1) corresponds to Equation 8 for the sample of Zip codes with at least 1 enrolled lender; column (2) corresponds to Equation 7, which includes both Black ratio and log number of PPP-enrolled lenders as regressors. Comparing across the two columns, the coefficient on Black Ratio, which measures the racial disparity in take-up, decreases for all zip code densities after controlling for the number of enrolled lenders. More specifically, the results suggest that access to enrolled lenders can explain 32.8% of the racial gap in low density areas, and 57.5% of the racial gap in medium density areas.

5 Conclusion

Many government support programs are designed to be intermediated by banks and credit unions. We show that one drawback of this design is that it exacerbates the distributional effects of "government support banking deserts". All else equal, neighborhoods with a greater share of Black population have fewer lenders, and the lenders that are present there are less likely to enroll in the PPP program. We show using an instrumental variables approach that the significantly lower take up rate of Black neighborhoods in lower population areas can be partially explained by this difference in access to enrolled lenders. Our results suggest that alternative implementations of government support programs, e.g. by combining "support through banks" with more outreach centers in banking deserts, or providing more incentives for credit unions in minority neighborhoods to participate in SBA programs, may improve the distributional impact of government support for small businesses.

Tables and Figures

Table 1: Summary statistics of our variables

	Mean	10th	Median	90th	N
Bank Presence					
Has Branch	0.69	0	1	1	28,969
Log(Branch)	1.10	0	1.10	2.40	19,951
Has Enrolled	0.64	0	1	1	28,969
Log(Enrolled)	0.98	0	0.69	2.20	18,520
Small Bank #	1.15	0	1	3	28,969
has_failed_branch	0.04	0	0	0	28,969
Demographics					
black_ratio	0.09	0.00	0.03	0.28	28,864
Log(Establishments)	4.25	1.79	4.22	6.71	28,969
Log(Population)	8.17	6.04	8.26	10.38	28,864
Population Density	4.81	2.08	4.43	8.16	28,175
PPP					
Takeup	0.60	0.33	0.60	1	28,969
Remote	0.12	0	0	1	4,696,969
log(Miles)	0.76	0	0	3.04	3,808,316

Note: this table shows the summary statistics of our Zip code level and PPP loan level samples. "Has Branch" is an indicator variable that is equal to one if a Zip code contains any branch, and "Log(Branch)" is the log number of branches (conditional on the number of branches being more than zero). "Has Enrolled" is an indicator variable that is equal to one if a Zip code contains any branch from a lender that enrolled in the PPP program, and "Log(Enrolled)" is the log number of branches from enrolled lenders (conditional on it being greater than zero). "Small Bank #" is the number of small banks (banks with less than or equal to 10 branches) operating in the Zip code in 2000 which we condition on in our failed small bank analysis, and "has_failed_branch" is an indicator variable for whether a Zip code was exposed to the failure of a small bank between October 2000 to 2019. In terms of demographics, "black_ratio" is the ratio of the population that is Black in a Zip code. "Log(Establishments)" is the log of number of small business establishments reported in in a ZBP data. "Log(Population)" is the log of the total population in a Zip Code Tabulation Area (ZCTA), and "Population Density" is the population density in a ZCTA. Finally, for PPP variables, "Takeup" is the ratio of loans taken out in a Zip code to the number of small establishments in the ZCTA. "Remote" is an indicator variable for whether the loan take out is from a remote lender (a lender whose nearest branch is more than 100 miles away). "Log(Miles)" is the log of 1 + number of miles from the small business to the nearest branch of their PPP lender, conditional on the number of miles being less than 100.

Table 2: Access to Lenders in Zip Code

	(1) Has Branch	(2) Has Branch	(3) Log(Branch)	(4) Log(Branch)
black_ratio	-0.0774***		-0.210***	
	(0.0215)		(0.0455)	
CZ_cat=1 × black_ratio		-0.219***		-0.185**
		(0.0507)		(0.0792)
CZ_cat=2 × black_ratio		-0.0864***		-0.176***
		(0.0332)		(0.0610)
CZ_cat=3 × black_ratio		-0.0212		-0.249***
		(0.0325)		(0.0756)
Constant	0.0293	0.0273	0.259***	0.287***
	(0.0365)	(0.0363)	(0.0509)	(0.0523)
2-digit NAICS controls	Yes	Yes	Yes	Yes
Log(Establishments) controls	Yes	Yes	Yes	Yes
Log(Population) controls	Yes	Yes	Yes	Yes
Population density	Yes	Yes	Yes	Yes
Observations	28136	27249	19237	18449
County FE	Yes	Yes	Yes	Yes

Robust standard errors clustered by county Zone in parentheses.

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

Note: This table shows OLS regressions of the presence of lenders (banks and credit union branches) in a Zip code. Column (1) is a regression of "Has Branch" on the ratio of Black population in the Zip code, black_ratio, with controls for the shares of 2-digit NAICS industry presence, log number of small establishments in the Zip code and squared, log population and squared, population density, as well as county fixed effects. Column (2) is the same regression but with black_ratio interacted with our three categories of commuting zone population. Columns (3) and (4) are the same regressions but on the intensive margin of the log number of branches in a Zip code, conditional on it being greater than zero.

Table 3: Access to Enrolled Lenders in Zip Code

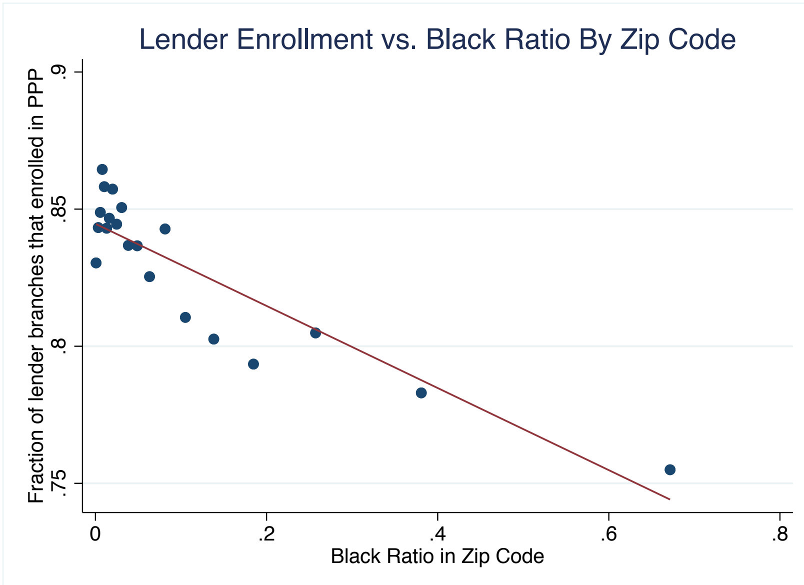
	(1) Has Enrolled	(2) Has Enrolled	(3) Log(Enrolled)	(4) Log(Enrolled)
black_ratio	-0.103***		-0.407***	
	(0.0225)		(0.0456)	
CZ_cat=1 × black_ratio		-0.259***		-0.477***
		(0.0492)		(0.0837)
CZ_cat=2 × black_ratio		-0.100***		-0.392***
		(0.0383)		(0.0644)
CZ_cat=3 × black_ratio		-0.0471		-0.412***
		(0.0322)		(0.0711)
Constant	-0.0360	-0.0277	0.457***	0.507***
	(0.0339)	(0.0351)	(0.0622)	(0.0621)
2-digit NAICS controls	Yes	Yes	Yes	Yes
Log(Establishments) controls	Yes	Yes	Yes	Yes
Log(Population) controls	Yes	Yes	Yes	Yes
Population density	Yes	Yes	Yes	Yes
Observations	28136	27249	17993	17232
County FE	Yes	Yes	Yes	Yes

Robust standard errors clustered by county in parentheses.

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

Note: This table shows OLS regressions of the presence of lenders (banks and credit union branches) enrolled in the PPP program in a Zip code. Column (1) is a regression of "Has Enrolled" on the ratio of Black population in the Zip code, black_ratio, with controls for the shares of 2-digit NAICS industry presence, log number of small establishments in the Zip code and squared, log population and squared, population density, as well as county fixed effects. Column (2) is the same regression but with black_ratio interacted with our three categories of commuting zone population. Columns (3) and (4) are the same regressions but on the intensive margin of the log number of enrolled lender branches in a Zip code, conditional on it being greater than zero.

Figure 1: Fraction of Branches in Zip Code Enrolled in PPP vs Ratio of Residents that are Black



Note: This figure shows a bin-scatter plot of the fraction of bank and credit union branches in a Zip code that enrolled in the PPP program on the y-axis and the ratio of residents in the Zip code that are Black on the x-axis.

Table 4: Probability of Enrollment by Branch

	(1) Enroll	(2) Enroll	(3) Enroll	(4) Enroll
black_ratio	-0.178***	-0.0411***		
	(0.0293)	(0.0120)		
CZ_cat=1 × black_ratio			-0.204***	-0.0778***
			(0.0444)	(0.0272)
CZ_cat=2 × black_ratio			-0.204***	-0.0371
			(0.0394)	(0.0231)
CZ_cat=3 × black_ratio			-0.156***	-0.0382***
			(0.0333)	(0.0139)
credit_union		-0.271***		-0.269***
		(0.0479)		(0.0488)
enrolled_sba		0.218***		0.210***
		(0.0322)		(0.0317)
small_lender		-0.0458**		-0.0461**
		(0.0213)		(0.0212)
credit_unionXsmall_lender		-0.249***		-0.255***
		(0.0404)		(0.0415)
credit_unionXenrolled_sba		0.274***		0.274***
		(0.0450)		(0.0457)
Constant	0.799***	0.794***	0.819***	0.804***
	(0.0513)	(0.0451)	(0.0512)	(0.0458)
2-digit NAICS controls	Yes	Yes	Yes	Yes
Log(estab) and squared	Yes	Yes	Yes	Yes
Log(Population) and squared	Yes	Yes	Yes	Yes
Population density	Yes	Yes	Yes	Yes
Observations	105047	105047	98721	98721
County FE	Yes	Yes	Yes	Yes

Robust standard errors clustered by lender and county in parentheses.

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

Note: This table shows the results of OLS regressions on branch enrollment. Column (1) is a regression of enrollment on the ratio of residents in a Zip code that are Black ("black_ratio") controlling for shares of 2-digit NAICS industries in a Zip code, log number of small establishments in a Zip code, log population in a Zip code, population density, and county fixed effects. Column (2) is the same regression but adds additional controls for whether the lender is a credit union, whether it is small (less than or equal to 10 branches), whether it is enrolled in the SBA 7a or 504 programs, and interactions of those variables. Columns (3) and (4) are the same regression as Columns (1) and (2), respectively, but interacted with categories of commuting zone population.

Table 5: Bank Branch Characteristics by Racial Composition of Neighborhood

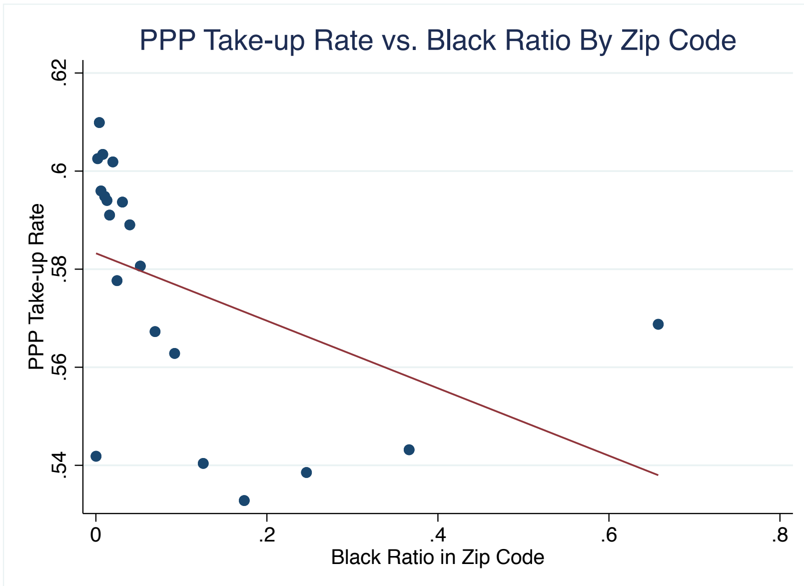
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Credit Union	Small Lender	Enrolled SBA	Credit UnionXSmall Lender	Credit UnionXEnrolled SBA	Small Lender, Excl CUs	Enrolled SBA, Excl CUs
black_ratio	0.220***	0.110***	-0.133***	0.180***	0.00742	-0.0598***	0.0487***
	(0.0347)	(0.0228)	(0.0277)	(0.0284)	(0.00607)	(0.0158)	(0.0165)
Constant	0.205***	0.602***	0.360***	0.0562	0.0867**	0.650***	0.374***
	(0.0574)	(0.0491)	(0.0545)	(0.0408)	(0.0379)	(0.0520)	(0.0528)
2-digit NAICS controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log(estab) and squared	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log(Population) and squared	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population density	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105047	105047	105047	105047	105047	83805	83805
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors clustered by lender and county in parentheses.

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

Note: This table shows the results of OLS regressions of black_ratio on indicator variables for the type of lender branches, including (1) Credit Union, (2) Small Lender (a lender with less than or equal to 10 branches), (3) a lender that is enrolled in SBA 7a or 504 programs, (4) the interaction of credit union and small lender, (5) the interaction of credit union and SBA enrollment, (6) small lender, conditional on non-credit union, and (7) a lender that is enrolled in SBA 7a or 504 programs, conditional on non-credit union. Control variables are 2-digit NAICS industries in a Zip code, log number of small establishments in a Zip code, log population in a Zip code, population density, and county fixed effects.

Figure 2: Fraction of small establishments in Zip code getting PPP loans vs. share of Black population in Zip code, binscatter plot



Note: This figure shows a bin-scatter plot of the fraction of small establishments in a Zip code that took out a PPP loan on the y-axis and the ratio of residents in the Zip code that are Black on the x-axis.

Table 6: Fraction of small establishments in a Zip code getting loans, by categories of commuting zone population

	(1) Takeup Rate	(2) Takeup Rate	(3) Takeup Rate	(4) Takeup Rate
black_ratio	-0.117***		-0.0844***	
	(0.0360)		(0.0294)	
CZ_cat=1 × black_ratio		-0.374***		-0.250***
		(0.0327)		(0.0300)
CZ_cat=2 × black_ratio		-0.204***		-0.134***
		(0.0292)		(0.0231)
CZ_cat=3 × black_ratio		-0.00607		-0.0228
		(0.0557)		(0.0468)
Constant	0.613***	0.621***	0.199***	0.207***
	(0.00334)	(0.00216)	(0.0258)	(0.0251)
2-digit NAICS controls	No	No	Yes	Yes
Log(Establishments) controls	No	No	Yes	Yes
Log(Population) controls	No	No	Yes	Yes
Population density	No	No	Yes	Yes
Observations	28864	27928	28136	27249
County FE	Yes	Yes	Yes	Yes

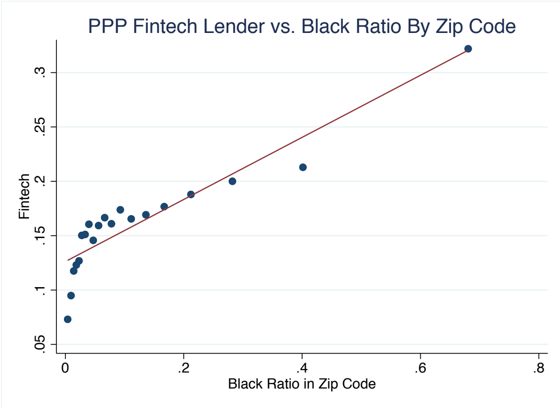
Robust standard errors clustered by county in parentheses.

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

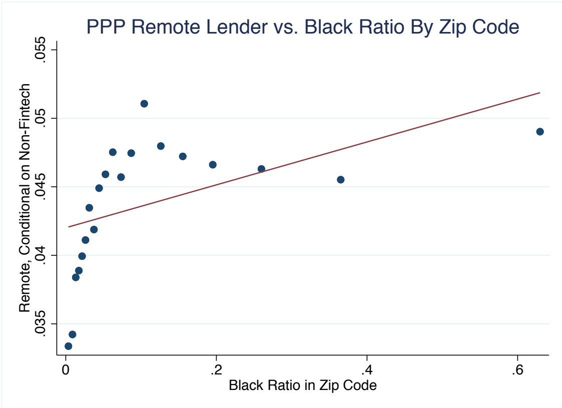
Note: This table shows OLS regressions on the PPP take-up rate in a Zip code. Column (1) is a regression of PPP take-up on the ratio of residents in a Zip code that are Black ("black_ratio") controlling only for county fixed effects. Column (2) is the same regression but interacted with categories of commuting zone population. Column (3) adds additional controls for shares of 2-digit NAICS industries in a Zip code, log number of small establishments in a Zip code, log population in a Zip code, and the population density. Column (4) is the same regression as Column (3) but interacted with our three categories of commuting zone density.

Figure 3: Type of PPP Lender used by Black Ratio in Zip Code

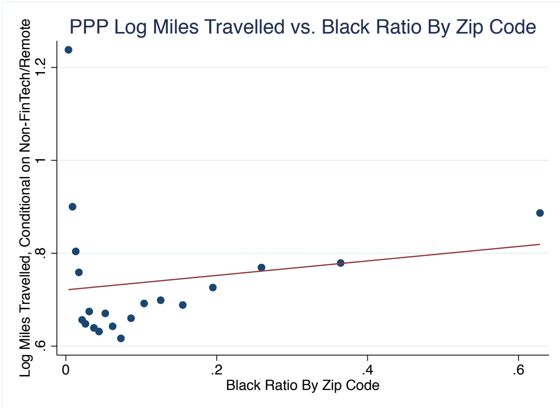
(a) Share of PPP Loans from Fintech Lender



(b) Conditional on Non-FinTech, share of PPP Loans from Remote Lender



(c) Conditional on Non-FinTech and Non-Remote, Log Miles to PPP Lender



Note: These figures show bin-scatter plot of the share of loans by PPP lender type on the y-axes, and the ratio of residents in the Zip code that are Black on the x-axis. Figure 3a shows whether the loan was taken out with a Fintech lender, Figure 3b shows whether the loan was taken out with a remote lender (a lender that is more than 100 miles away from the small business) conditional on non-Fintech, and Figure 3c shows the log miles travelled to the lender (the distance between the business and the nearest lender branch) conditional on non-Fintech and non-Remote.

Table 7: Type of PPP Lender Used Regressions

	(1) FinTech	(2) FinTech	(3) Remote	(4) Remote	(5) Log(Miles)	(6) Log(Miles)
black_ratio	0.166***		0.00872***		0.244***	
	(0.0248)		(0.00270)		(0.0252)	
CZ_cat=1 × black_ratio		0.0528***		0.00784		0.417***
		(0.00727)		(0.00507)		(0.0817)
CZ_cat=2 × black_ratio		0.100***		-0.00371		0.210***
		(0.0142)		(0.00663)		(0.0556)
CZ_cat=3 × black_ratio		0.206***		0.0134***		0.242***
		(0.0350)		(0.00276)		(0.0291)
Constant	0.184***	0.143***	0.0305***	0.0230**	3.013***	2.869***
	(0.0275)	(0.0264)	(0.0109)	(0.0108)	(0.145)	(0.144)
2-digit NAICS controls	Yes	Yes	Yes	Yes	Yes	Yes
Log(Establishments) controls	Yes	Yes	Yes	Yes	Yes	Yes
Log(Population) controls	Yes	Yes	Yes	Yes	Yes	Yes
Population density	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4342923	3880797	3896283	3528177	3724185	3377126
County FE	Yes	Yes	Yes	Yes		

Robust standard errors clustered by county in parentheses.

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

Note: Column (1) of this table displays the result of an OLS regression on an indicator variable for whether the loan was taken out with a Fintech lender and the ratio of Black residents in the Zip code ("black_ratio"), controlling for 2-digit NAICS shares, log number of establishments in a Zip code and squared, log population and squared, population density, and county fixed effects. Column (2) is the same regression but with black_ratio interacted with our categories of commuting zone density. Column (3) displays the results of an OLS regression on an indicator variable for whether the loan was taken out with remote lender (a lender whose nearest branch is more than 100 miles away) conditional on non-Fintech, with the same dependent variables as Column (1). Column (4) is the same regression but with black_ratio interacted with our categories of commuting zone density. Column (5) is the same regression as Column (3) but with the dependent variable changed to log 1 + number of miles to the nearest branch of the PPP lender, conditional on non-Fintech and non-remote. Column (6) is the same regression as Column (5) but with black_ratio interacted with our categories of commuting zone density.

Table 8: Instrumental variables first stage estimates

	(1) Has Enrolled	(2) Log(Enrolled)
has_failed_branch	-0.00290	0.0908***
	(0.00889)	(0.0151)
Constant	-0.0560*	0.312***
	(0.0316)	(0.0622)
2-digit NAICS controls	Yes	Yes
Log(Establishments) controls	Yes	Yes
Log(Population) controls	Yes	Yes
Population density	Yes	Yes
Small Bank # controls	Yes	Yes
Observations	27957	17397
County FE	Yes	Yes

Robust standard errors clustered by county in parentheses.

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

Note: this table shows our first stage regressions of an indicator variable for whether a Zip code has an enrolled lender in Column (1), and the log number of enrolled branches (conditional on there being at least one) in Column (2). We control for 2-digit NAICS shares, log number of small establishments and squared, log population and squared, population density, and the 2000 number of small banks in the Zip code and squared, and county fixed effects.

Table 9: Instrumental Variables Second Stage Estimates

	(1) Takeup	(2) Takeup
Log(Enrolled)	0.119**	
	(0.0505)	
CZ_cat=1 $\times$ Log(Enrolled)		0.118**
		(0.0599)
CZ_cat=2 $\times$ Log(Enrolled)		0.149***
		(0.0546)
CZ_cat=3 $\times$ Log(Enrolled)		0.126**
		(0.0533)
2-digit NAICS controls	Yes	Yes
Log(Establishments) controls	Yes	Yes
Log(Population) controls	Yes	Yes
Population density	Yes	Yes
Small Bank # controls	Yes	Yes
Observations	17397	16638
First stage F-stat	36.09	10.39
County FE	Yes	Yes

Robust standard errors clustered by county in parentheses.

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

Note: this table shows our second stage regressions of take up on the log number of enrolled branches (conditional on there being at least one) in Column (1), and the log number of enrolled branches (conditional on there being at least one) interacted with our Commuting Zone population category in Column (2). We control for 2-digit NAICS shares, log number of small establishments and squared, log population and squared, population density, the 2000 number of small banks in the Zip code and squared, and county fixed effects.

Table 10: Instrumental Variables Implication

	(1) Takeup	(2) Takeup
CZ_cat=1 × black_ratio	-0.241***	-0.162***
	(0.0306)	(0.0406)
CZ_cat=2 × black_ratio	-0.0817***	-0.0367
	(0.0223)	(0.0285)
CZ_cat=3 × black_ratio	0.0512	0.0955
	(0.0532)	(0.0585)
CZ_cat=1 × Log(Enrolled)		0.112*
		(0.0598)
CZ_cat=2 × Log(Enrolled)		0.140**
		(0.0546)
CZ_cat=3 × Log(Enrolled)		0.123**
		(0.0540)
Constant	0.424***	
	(0.0479)	
2-digit NAICS controls	Yes	Yes
Log(Establishments) controls	Yes	Yes
Log(Population) controls	Yes	Yes
Population density	Yes	Yes
Small Bank # controls	Yes	Yes
Observations	16638	16638
First stage F-stat		10.32
County FE	Yes	Yes

Robust standard errors clustered by county in parentheses.

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

Note: Column (1) of this table is an OLS regression of take-up on the ratio of the population that is Black ("black_ratio") interacted with our categorical variable for Commuting Zone density within the Zip codes with at least one enrolled lender, controlling for 2-digit NAICS shares, log number of small establishments and squared, log population and squared, population density, the 2000 number of small banks in the Zip code and squared, and county fixed effects. Column (2) is the second stage of an IV regression that adds in the log of the number of enrolled branches interacted with our categories of Commuting Zone population.

References

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A Additional Tables and Figures

Table A1: List of FinTech lenders

FinTech Lender	Count of Round 1+2 PPP Loans
BSD Capital, LLC dba Lendistry	3542
CRF Small Business Loan Company, LLC	2396
Celtic Bank Corporation	147258
Centerstone SBA Lending, Inc.	898
Cross River Bank	193370
Customers Bank	69293
Evolve Bank & Trust	706
FC Marketplace, LLC (dba Funding Circle)	6140
Fountainhead SBF LLC	2768
Fund-Ex Solutions Group, LLC	1388
Fundbox, Inc.	14234
Grow America Fund, Incorporated	704
Harvest Small Business Finance, LLC	5342
Intuit Financing Inc.	18562
Kabbage, Inc.	161189
LendingClub Bank, National Association	5478
Loan Source Incorporated	193
NBKC Bank	484
Newtek Small Business Finance, Inc.	11540
Readycap Lending, LLC	34261
Sunrise Banks, National Association	1838
The Bancorp Bank	1288
VelocitySBA, LLC	108
WebBank	76421
immito, LLC	293

Note: This table lists the lenders we classified as FinTech and the sum of their round 1 and 2 PPP loans. This list is in part based on Howell, Kuchler, and Stroebel (2021).

Table A2: Type of PPP Lender Used Regressions, name assigned business owner race

	(1) FinTech	(2) FinTech	(3) Remote	(4) Remote	(5) Log(Miles)	(6) Log(Miles)
black_assign	0.241***		0.0289*		0.131*	
	(0.0155)		(0.0165)		(0.0783)	
CZ_cat=1 × black_assign		0.365***		0.00342		-0.0461
		(0.0354)		(0.0315)		(0.152)
CZ_cat=2 × black_assign		0.300***		0.0567		0.127
		(0.0189)		(0.0388)		(0.150)
CZ_cat=3 × black_assign		0.221***		0.0285		0.226*
		(0.0197)		(0.0229)		(0.124)
Constant	0.405***	0.409***	0.0291	0.0276	2.856***	2.814***
	(0.0400)	(0.0419)	(0.0191)	(0.0194)	(0.193)	(0.197)
2-digit NAICS controls	Yes	Yes	Yes	Yes	Yes	Yes
Log(Establishments) controls	Yes	Yes	Yes	Yes	Yes	Yes
Log(Population) controls	Yes	Yes	Yes	Yes	Yes	Yes
Population density	Yes	Yes	Yes	Yes	Yes	Yes
Observations	438028	396688	269060	254038	255545	242056
County FE	Yes	Yes	Yes	Yes		

Robust standard errors clustered by county in parentheses.

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

Note: Column (1) of this table displays the result of an OLS regression on an indicator variable for whether the loan was taken out with a Fintech lender on an indicator variable for borrower race assigned based on their first name, last name, and county, controlling for 2-digit NAICS shares, log number of establishments in a Zip code and squared, log population and squared, population density, and county fixed effects. Column (2) is the same regression but with black_ratio interacted with our categories of commuting zone density. Column (3) displays the results of an OLS regression on an indicator variable for whether the loan was taken out with remote lender (a lender whose nearest branch is more than 100 miles away) conditional on non-FinTech, with the same dependent variables as Column (1). Column (4) is the same regression but with the black dummy interacted with our categories of commuting zone density. Column (5) is the same regression as Column (3) but with the dependent variable changed to log 1 + number of miles to the nearest branch of the PPP lender, conditional on non-Fintech and non-remote. Column (6) is the same regression as Column (5) but with black_ratio interacted with our categories of commuting zone density.

Table A3: Instrumental variables first stage estimates

	(1) Has Enrolled	(2) Log(Enrolled)
has_failed_branch	-0.00290	0.0908***
	(0.00889)	(0.0151)
Constant	-0.0560*	0.312***
	(0.0316)	(0.0622)
2-digit NAICS controls	Yes	Yes
Log(Establishments) controls	Yes	Yes
Log(Population) controls	Yes	Yes
Population density	Yes	Yes
Small Bank # controls	Yes	Yes
Observations	27957	17397
County FE	Yes	Yes

Robust standard errors clustered by county in parentheses.

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

Note: this table shows our first stage regressions of an indicator variable for whether a Zip code has an enrolled lender in Column (1), and the log number of enrolled branches (conditional on there being at least one) in Column (2). We control for 2-digit NAICS shares, log number of small establishments and squared, log population and squared, population density, and the 2000 number of small banks in the Zip code and squared, and county fixed effects.

Table A4: Failed branch and pre-COVID unemployment insurance claim rate

	(1) Feb UI Rate	(2) Takeup Rate
has_failed_branch	0.00265	
	(0.00232)	
claim_rate_feb		-0.100***
		(0.0357)
Constant	0.251***	0.224***
	(0.0110)	(0.0372)
2-digit NAICS controls	Yes	Yes
Log(Establishments) controls	Yes	Yes
Log(Population) controls	Yes	Yes
Population density	Yes	Yes
Small Bank # controls	Yes	Yes
Observations	12283	12283
Commuting Zone FE	Yes	Yes

Robust standard errors clustered by County FIPS in parentheses.

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

Note: Column (1) of this table is an OLS regression of the Zip code-level unemployment claim rate in February 2020 on a dummy variable that is equal to one if the Zip code contains at least one branch of a failed small bank, where a small bank is defined as a bank with fewer than 10 branches. Column (2) of this table is an OLS regression of the Zip code-level take-up rate on the unemployment claim rate in Febraury 2020. Both regressions control for 2-digit NAICS shares, log number of small establishments and squared, log population and squared, population density, the 2000 number of small banks in the Zip code and squared, and Commuting Zone fixed effects.

B Small Business Survey

Q1.1: This small business survey has been explained to me. I know that I may refuse to participate or to stop the interview at any time without repercussions of any kind. I agree to participate:

Basic Information:

Q2.1: Did you own a business in **February 2020**, prior to the pandemic?

Q2.2: Please enter the name of your business: ______

Q2.3: Please enter the zip code of your business: ______

Q2.1: What was the state of your business between **February 2020** and **May 2020**?

1. My business was permanently closed
2. My business was temporarily closed but reopened
3. My business was open, but I considered closing
4. My business was open, and I did not consider closing at any point

Financial Institution and PPP:

Q3.1: What was the name of your primary bank, credit union, or financial institution? ___________

Q3.2: Did you receive information about Paycheck Protection Program (PPP) loans from your primary bank, credit union, or financial institution?

- Yes, through email
- Yes, through conversations with someone at the bank
- No

Q3.3 (if Q3.2 = No): How did you learn of the PPP?

- I have previously applied to other programs implemented by the Small Business Administration (SBA)
- A bank, credit union, or financial institution other than my primary one
- News Media
- Social Media
- I have not heard of PPP

PPP Application

Q4.1 Did you apply to the Paycheck Protection Program (PPP) between **February 2020** and **May 2020**?

Q4.2 (if Q4.1 = Yes): Did you use your primary bank, credit union, or financial institution to apply for PPP?

- Yes
- No

Q4.3 (if Q4.1 = Yes and Q4.2 = No): Through which bank, credit union, or financial institution did you apply for PPP? __________

If (Q4.1 = Yes):

Q5.1: On a scale of 0 to 10, please rate how difficult is it to apply:

Q5.2: On a scale of 0 to 10, please rate how helpful your loan officer during the application process?

Q5.3: When did you first apply to the program? (MM/DD/YYYY)

Q5.4: When did you hear back from your application? (MM/DD/YYYY)

Q5.5: What was the outcome of your application?

- My application was approved and I received the funding
- My application was rejected
- I was notified that funds are no longer available
- Other (please explain): _________________________

If (Q4.1 = No):

Q5.5: Why did you decide to not apply? (Select all options that apply.)

- I was not eligible for the PPP
- I was not eligible for loan forgiveness
- I did not know if I am eligible for PPP
- I was unsure if I was eligible for loan forgiveness
- I did not know how to apply

Important other information

Q6.1: Which of the following best describes you?

- Asian or Pacific Islander
- Black or African American
- Hispanic or Latino
- Native American or Alaskan Native
- White or Caucasian
- Multiple races
- Some other race, ethnicity, or origin

Q6.2: Which sector best describes your business?

- Restaurant
- Retail
- Manufacturing
- Services
- Agriculture
- Construction
- Other (please specify): _____________

Q6.3: What type of business do you or did you own?

- Sole proprietor
- Independent Contractor
- Partnership
- C-Corp
- S-Corp
- LLC
- Self-employed individual
- Non-profit
- I am not sure

Q6.4: How many employees worked at the business you own in February 2020?

Number of full-time employees: _______________

Number of part-time employees: ______________

Q6.5: Did you lay off or consider laying off any employees between February 2020 and May 2020?

- Yes, I laid off workers
- I considered laying off workers but ended up not laying off
- No, I did not lay off workers

Q6.6: How many people did you lay off?

Other demographics

Q7.2: What is the highest educational level you have achieved?

- Less than high school
- High school graduate
- Some college
- 2-year college degree
- 4-year college degree
- Professional degree
- Master's degree
- Doctoral degree

Q7.3: What is your sex?

- Female
- Male

Q7.4: What is your age group?

- 18-24
- 25-34
- 34-49
- 50+

Q8: Do you have any other comments about government support during the pandemic?