Racial Disparities in the Paycheck Protection Program*

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Abstract

Using a large sample of Florida restaurants, we document significant racial disparities in the utilization of the Paycheck Protection Program (PPP). Only a small fraction of these disparities can be explained by distance to bank branches. Within the same ZIP code, Black- and Hispanic-owned firms are 20.5% and 7.0% less likely than white-owned firms to receive PPP loans. These disparities in PPP utilization are driven by disparities in bank lending, which are greater in counties in which white people exhibit more racial bias against Black people. In these more racially biased counties, Black-owned businesses substitute to nonbank PPP loans and loans provided directly by the Small Business Administration through its Economic Injury Disaster Loan program.

Keywords: discrimination, Paycheck Protection Program, Economic Injury Disaster Loans, bank lending, nonbank lending

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1 Introduction

A key component of the federal government's response to the negative economic effects of the COVID-19 pandemic was the Paycheck Protection Protection (PPP), authorized by the CARES Act in March 2020 and later extended and enhanced in subsequent legislation. Under PPP, the Small Business Administration (SBA) guaranteed $800 billion in low-interest rate loans made by financial institutions to businesses with up to 500 employees, and promised to forgive these loans if borrowers maintain employment and certain other fixed expenses. A number of studies have examined whether PPP loans were made to businesses that were most in need of such loans and whether they succeeded in mitigating the economic effects of the pandemic (Autor et al. (2020); Bartik et al. (2020); Granja et al. (2020); Li and Strahan (2021); Hubbard and Strain (2021)).

Politicians, journalists and community groups have argued that Black and Hispanic business owners had unequal access to PPP loans.[1] One concern is that these businesses were disadvantaged because they tend to have weaker relationships to banks, stemming in part from a history of discrimination and in part because they are located in areas with fewer bank branches. Another concern is that Black and Hispanic business owners received discriminatory treatment from lenders when applying for PPP loans. (National Community Reinvestment Coalition, 2020b,a).

Academic research has claimed evidence of racial disparities in PPP access based on comparisons of the take-up rate across geographic areas with different shares of minority populations. Wang and Zhang (2020), for example, show that ZIP codes with a greater percentage of Black residents had lower take-up rates of PPP loans, measured by the ratio of PPP loans to the number of establishments in a ZIP code. The lower take-up rate is related to a lower concentration of branches of PPP-approved lenders in ZIP codes with more Black residents. Consistent with this finding, Erel and Liebersohn (2020) document that fintech lenders originated a larger share of PPP loans in ZIP codes with a larger minority population share. While these findings are important in that they suggest that there are structural inequities in access to PPP funding, this approach cannot answer the question of whether business owners within a ZIP code face differential access based on race, which may be even more important than proximity to PPP lenders. Furthermore, this approach does not control for differences in firm characteristics across geographies, which may affect

[1] See, for example, Flitter, "Black-Owned Businesses Could Face Hurdles in Federal Aid Program" *New York Times*, April 10, 2020, https://www.nytimes.com/2020/04/10/business/minority-business-coronavirus-loans.html.

both demand and supply of PPP loans. And, finally, the measure of the take-up rate itself is noisy, which could result in either understated or overstated estimates of the impact of race on PPP lending.

In this paper, we provide the first systematic micro-level evidence showing that Black- and Hispanic-owned businesses are less likely to receive PPP loans than white-owned businesses. We do so by exploiting Florida data on restaurant licenses, corporate records, and voter registration. Restaurant license data give us the population of restaurants in Florida that are eligible to use PPP loans. From corporate records we are able to determine the identity of the restaurant owner. Finally, voter registration data tell us restaurant owners' self-identified race or whether they are of Hispanic origin, information that is sparsely reported in PPP data.[2] By putting together all of these data, we are able to estimate the relationship between PPP lending and a restaurant owner's racial or Hispanic identity, as well as how characteristics of the local banking market affect this relationship. Data on the firms' existing secured loans also enable us to examine the effect of prior lending relationships on access to PPP loans.

We show that Black- and Hispanic-owned restaurants are 26.2% and 10.1% less likely to receive PPP loans than white-owned restaurants. Restaurants owned by those who self-identify as Asian/Pacific Islander are 1.7% less likely than white-owned restaurants to receive PPP loans; this difference is not statistically significant. We also find that restaurants owned by women are 4.9% less likely to receive PPP loans.

One possible explanation of these findings is that Black- and Hispanic-owned restaurants are located in areas with fewer bank branches. However, we show that location explains only a modest portion of the differences in PPP utilization. Within a ZIP code, Black-, Hispanic-, and female-owned restaurants are still 20.5%, 7.0%, and 4.0% less likely to receive PPP funding. All of these differences are highly statistically significant. Thus, being located in under-banked ZIP codes, as suggested by prior studies (Wang and Zhang, 2020), is only part of the reason why Black- and Hispanic-owned businesses are less likely to receive PPP loans. These disparities exist even within much smaller geographic areas such as Census blocks. They also exist after controlling for restaurant size and age, although these controls reduce the estimated disparities to 14.5% for Black-owned restaurants, 4.9% for Hispanic-owned restaurants, and 2.3% for restaurants owned by women.

[2] Registered voters in Florida are asked to indicate whether they are Black (not of Hispanic origin), Hispanic, White (not of Hispanic origin), Asian/Pacific Islander, American Indian/Alaska native, Multi-racial, or Other. These categories contrast with the current Census designations, which separate the concepts of race and Hispanic origin.

We next show that disparities in PPP utilization are driven by disparities in bank lending, and that nonbank PPP lenders—largely fintechs—tend to offset these disparities by lending at greater rates to minority-owned restaurants. In particular, Black- Hispanic- and female-owned restaurants are 19.9%, 4.8% and 3.4% less likely than white-owned restaurants to receive bank PPP loans, controlling for ZIP code and restaurant characteristics. By contrast, Black- and female-owned restaurants are 5.5% and 1.2% more likely to receive nonbank PPP loans. Hispanic-owned restaurants are not more likely than white-owned restaurants to receive nonbank PPP loans. Interestingly, while Asian-owned restaurants receive PPP loans at the same rate as white-owned restaurants, they are 5.3% less likely to borrow from banks and 7.6% more likely to borrow from nonbanks. Given that the higher rate of nonbank lending to Black- and Asian-owned restaurants exists both across and within ZIP codes, it indicates that nonbanks are not just filling in for banks in locations where they are less prevalent, as suggested by Erel and Liebersohn (2020), but also lending to groups that are less likely to receive bank financing even when there are nearby banks.

In addition to receiving nonbank PPP financing at greater rates, minority restaurant owners are more likely to receive funding from the Economic Injury Disaster Loans (EIDL) program, an existing SBA disaster relief program that helps firms pay financial obligations and operating expenses that could have been paid if a disaster had not occurred. Firms apply directly to the SBA through its website rather than through a financial intermediary. The CARES Act authorized use of EIDL loans for small businesses impacted by the Covid pandemic. Although the Act loosened some requirements to get an EIDL loan, a number of features of EIDL loans make them less desirable than PPP loans. For one, EIDL loans are not forgivable. In addition, these loans carry higher interest rates than PPP loans (3.75% versus 1.00%), require collateral and, in some cases, personal guarantees. Nevertheless, the SBA has granted EIDL loans of about $229 billion, disproportionately to Hispanic-owned restaurants (4.8%) and Asian-owned restaurants (3.1%). Indeed, conditional on receiving some kind of emergency loan (EIDL or PPP), minority-owned restaurants are considerably more likely to receive nonbank PPP funding or EIDL funding than they are to receive bank PPP funding: 22.2% more likely for Black-owned restaurants, 6.8% for Hispanic-owned restaurants, 9.5% for Asian-owned restaurants, and 3.0% for female-owned restaurants.

The evidence that minority-owned restaurants receive nonbank PPP loans and EIDL loans at greater rates than white-owned restaurants cuts against a potential explanation of our findings—namely, that the the overall lower rate of PPP utilization by minority-owned restaurants could be explained by their lower demand for emergency loans. If they did have lower demand for emergency loans, then we would expect to see lower take-up rates across

the board, including bank PPP loans, nonbank PPP loans and EIDL loans. The fact that we just observe lower take-up rates in bank PPP loans suggests either that banks are less willing than other lenders to fund minority-owned businesses or that minority business owners find applying for bank PPP loans less desirable.

We explore two potential explanations for the lower rate of bank PPP lending to minority-owned businesses: (i) weaker relationships between minority-owned businesses and banks prior to the pandemic; (ii) racial bias. Weaker relationships could explain the findings if banks prioritized their relationship clients at a time when banks had limited capacity to process applications. While we cannot measure the full scope of a banking relationship, which could include loans of different types, business checking accounts, and merchant services, we can use Uniform Commercial Code (UCC) filings to determine whether a firm had any secured loans other than a mortgage. We find that white-owned restaurants are 11.9% more likely to get a PPP loan from a bank if they have an existing secured bank loan and 5.3% more likely if they have an existing nonbank secured loan. While minority-owned restaurants are indeed less likely to have secured loans outstanding, controlling for these lending relationships has only a modest impact on the disparities in PPP lending. In fact, Black-owned restaurants with outstanding secured loans are no more likely than those without such loans to receive bank PPP funding. This finding suggests that banks either do not prioritize Black-owned businesses with which they have a lending relationship or that Black business owners are more dissatisfied with their bank lender and thus less likely to apply for a PPP loan from a bank. This latter explanation is consistent with the results of surveys indicating that Black business owners are less satisfied with their financial services providers (Federal Reserve Banks, 2021).

The final hypothesis is that the results are explained by racial bias. It is possible that racial bias exists in the PPP loan application process at banks. It is also possible that a history of racial bias discouraged minority business owners from applying for bank PPP loans. To explore the role of racial bias, we examine whether racial disparities in bank PPP loans are greater in counties that appear to be more racially biased. We use measures of implicit and explicit racial bias from Project Implicit, which offers online tests to measure a person's implicit associations and biases.[3] Our findings indicate that Black-owned restaurants in counties in which white test-takers exhibit more explicit and implicit bias against Black people are significantly less likely to receive PPP funding from banks. The effect is large: a one standard deviation increase in explicit (implicit) bias is associated with a 19.1 (22.8)

[3] https://implicit.harvard.edu/implicit/takeatest.html

percentage-point reduction in the probability that a Black-owned restaurant receives a PPP loan from a bank. Given that a Black-owned restaurant in a county with an average level of explicit (implicit) racial bias is 25.2% (17.5%) less likely to get a PPP loan, this implies that Black-owned restaurants in the more racially biased counties are 44.3% (40.3%) less likely to get a bank PPP loan than white-owned restaurants.

What explains the association between racial bias and disparities in the utilization of bank PPP loans? It could be that local racial bias negatively affects consumer demand for Black-owned restaurants, making it uneconomical for the restaurants to stay open even if they received PPP funding. We rule out such demand-side explanations by showing that local racial bias is associated with a significantly higher take-up of nonbank PPP loans and EIDL program loans by Black-owned restaurants. Thus, in areas with greater racial bias, Black-owned restaurants substitute from bank PPP loans to nonbank PPP loans and EIDL loans, both of which involve less personal interaction in the application process. We also show that when Black-owned restaurants in more racially-biased counties do receive PPP loans from banks, those banks are likely to be located farther away from the restaurant, suggesting that Black-owned restaurants have to search more than white-owned restaurants for bank PPP loans. Finally, we examine whether Biden administration efforts in the third round of PPP to reduce racial disparities— largely by prioritizing lending through financial institutions with closer ties to minority communities—had the intended effect. We show that racial disparities were attenuated, particularly for Black-owned restaurants, although disparities remain. We also do not find that there were greater racial disparities in more racially biased counties.

Our findings on racial bias are consistent with the existence of racial discrimination in the processing of PPP applications. Indeed, audit studies by the National Community Reinvestment Coalition (NCRC) provide evidence that Black, Hispanic and female business owners received worse treatment from banks in response to questions about PPP loans (National Community Reinvestment Coalition, 2020b,a). Negative treatment at the initial stage may have also reduced the likelihood that minority-owned businesses applied for bank PPP loans for fear of being turned down.[4] It is also possible that while there was no discrimination conditional on applying for a bank PPP loan, a legacy of past discrimination and poor treatment may have discouraged minority-owned businesses, particularly Black-owned businesses, from even approaching banks for a PPP loan.

[4] An earlier literature on racial discrimination in the National Survey of Small Business Finances finds that Black- and Hispanic-owned businesses are 40% and 23% more likely to say that they did not apply for a loan because they feared denial (Blanchflower, Levine, and Zimmerman, 2003).

Finally, one may wonder about the external validity of our results. Is there something special about restaurants or are the results likely to apply to other industries? While we do not have a well-defined population of eligible firms in other industries to study variation in PPP take-up rates, we can study disparities in bank PPP loans within the population of Florida firms that receive either PPP or EIDL loans. In other words, we can ask the following question: conditional on receiving a COVID-19 emergency loan, does race affect the source of the emergency loan? We find very similar results to our sample of restaurants. Controlling for ZIP code cross industry fixed effects, firm age, sales, employees, and secured lending relationships, Black-, Hispanic-, and Asian-owned businesses are 22.8% 12.0%, and 3.4% less likely to receive bank PPP loans. Thus, our results are likely to apply to all firms and not just restaurants.

In addition to contributing to the growing literature on the Paycheck Protection Program, our paper contributes to a broader literature on discrimination in small business lending. Blanchflower, Levine, and Zimmerman (2003); Cavalluzzo and Wolken (2005); Blanchard, Zhao, and Yinger (2008), among others, use National Surveys of Small Business Finances to show that Black- and Hispanic-owned businesses are more likely than white-owned businesses to be turned down for bank loans, controlling for a host of firm characteristics including credit ratings and the personal wealth of the business owner. While we do not have data on the firms' credit ratings and financials, standard measures of creditworthiness would seem to be less relevant here given that the ability to repay a loan was not supposed to be a criterion for receiving a PPP loan. Rather than studying loan application denial rates, we account for loan demand by comparing utilization of bank PPP loans with nonbank PPP loans and EIDL program loans. Finally, we show that disparities in bank lending are stronger in areas with greater racial bias.

The rest of the paper is organized as follows. Section 2 describes our data and reports basic summary statistics. Section 3 presents the results of our baseline analyses of racial disparities using data on Florida restaurants. We examine whether differences in bank relationships could explain racial disparities in Section 4 and then examine the role of racial bias in Section 5. Section 6 examines the robustness of our findings to the inclusion of detailed information on restaurant characteristics and pre-pandemic customer visits, alternative restaurant samples, and more detailed geographic controls. We also consider the external validity of our findings to a broader sample of Florida businesses. Section 7 concludes.

2 Data

Our main data set is composed of restaurants in Florida with information on the owner's identity and on whether the restaurant received loans from the Paycheck Protection Program (PPP) or the COVID-19 Economic Injury Disaster Loan (EIDL) program, both sponsored by the SBA. The EIDL program offers long-term low interest loans to firms that are adversely affected by a disaster such as the COVID pandemic. Unlike PPP, the loans are not forgivable and firms apply directly to the SBA for approval.

We construct the data set by combining data on: 1) approved PPP loans, 2) approved EIDL loans, 3) Florida restaurant licenses, 4) Florida corporate records, and 5) Florida voter registration data.

2.1 PPP and EIDL loans

Data on approved loans from PPP and the EIDL program are from the SBA website.[5] PPP loan data include all loans approved during the periods April 3–August 9, 2020 and January 11–June 30, 2021. EIDL data include loans approved through November 14, 2020. The SBA has not yet released loan-level data on the EIDL program loans made after this date. The aggregate number and value of EIDL loans made in 2021—3.8 million loans worth $211 billion—are very similar to the number and value of loans made in 2020: 3.6 million loans worth $194 billion. Most of our analyses compare PPP and EIDL loans extended during 2020. Both PPP and EIDL data report the borrower's name and location, loan amount and approval date. PPP loan data also report the lender's name and location, borrower's industry, as well as self-reported demographic information on the borrower. However, the vast majority of PPP borrowers (83%) do not to report information on racial or Hispanic identity.

After limiting the sample to borrowers located in Florida and excluding non-profits, we match borrowers by name to Florida corporate records.[6] Details of the matching algorithm are described in the Appendix. We are able to identify 87.9% of all PPP borrowers and 84.5% of all EIDL borrowers. Most of the unmatched borrowers are individuals.

[5] PPP loan data are available at https://sba.app.box.com/s/5myd1nxutoq8wxecx2562baruz774si6, EIDL loans data are available at https://data.sba.gov/dataset/covid-19-eidl

[6] Florida borrowers account for 7.8% of all PPP loans.

2.2 Potential borrowers

Much of the existing research on the Paycheck Protection Program is constrained by the fact that most eligible borrowers are small private firms about which there is relatively limited data. One way that researchers have tried to address this challenge is by conducting surveys (Bartik et al., 2020). However, existing surveys are limited in size and may include relatively few minority-owned businesses.[7] Another approach is to examine the factors that drive variation in the PPP loan take-up rate across geographic areas, where the take-up rate is measured as the number of PPP borrowers relative to the number of establishments in the area. See, for example, Wang and Zhang (2020) and Erel and Liebersohn (2020). This approach cannot control for firm characteristics that could affect loan demand or supply, and it cannot analyze the factors that affect PPP utilization within a geographic area. For example, it is possible that a ZIP code with a large Black population has relatively few bank branches, but banks within the ZIP code treat all groups equally. County- or ZIP-code level take-up rates are also subject to measurement error that could result in either understated or overstated estimates of the impact of race on PPP lending.[8]

We overcome these limitations of the existing research by studying the utilization of PPP and EIDL loans by Florida restaurants.[9] Because essentially all restaurants were eligible for PPP and EIDL loans and because Florida restaurants are subject to state licensing, we have comprehensive and reliable data on the population of eligible firms. We obtain the list of all Florida restaurant licenses from the Florida Department of Business & Professional Regulation.[10]

To have a relatively homogeneous sample, we focus on restaurants that offer seating and exclude food trucks, take-out only restaurants without seating, and caterers. We exclude

[7] Bartik et al. (2020) for example conduct their survey through Alignable, a network of almost five million small businesses. They receive 6,137 valid responses, for a response rate of 12 basis points, and are unable to break out the results for minority business owners because of their small numbers in the data.

[8] This ratio is a noisy measure of the take-up for a few reasons. First, not all establishments were eligible for PPP loans. Second, a given establishment and its owner can reside in different geographic areas. Third, a given firm can own multiple establishments. Simple measurement error in the dependent variable will result in larger standard errors that will make it more difficult to find any statistically significant results. But measurement error can be correlated in complicated and unknown ways with the area's demographics. For example, if in poorer areas, with larger shares of racial minorities, establishments are more likely to be owned by companies with headquarters outside the area, take-up of PPP loans will be understated, inducing a spurious negative correlation between the take-up rate and the minority share of the population.

[9] Restaurants, defined as borrowers with NAICS codes starting with 722, account for 6.4% of all PPP loans.

[10] http://www.myfloridalicense.com/DBPR/hotels-restaurants/public-records/

restaurants with licenses approved after February 15, 2020, hotel restaurants, and franchise restaurants. Because hotel and franchise restaurants are frequently owned and operated by affiliated entities, it is often difficult to determine whether a given hotel or franchise restaurant received an emergency loan. Even if the license holder did not receive an emergency loan, it is possible that its parent or affiliate did.[11] To minimize error in determining which restaurants received emergency loans we therefore exclude hotel and franchise restaurants. Restaurants are classified as being in a hotel if they share the same address as one of the hotels in Florida hotel license data.[12] We classify restaurants as franchises based on restaurant names.

Restaurant license data identify the name and location of the restaurant as well as the license holder. We match license holders to Florida corporate records. Most license holders are firms, enabling a straightforward match based on their name and location. In some cases the license holder is an individual. We attempt to match these individuals to Florida corporate records based on the name of the firm's first listed officer or director. Because a given person can serve as an officer or director of multiple firms, we consider only unique matches, i.e, cases where the restaurant license holder is an officer or director of only one firm in Florida corporate records. Overall, we are able to match 93.6% of restaurants that meet the sample selection criteria to Florida corporate records. Most of the remaining restaurants list individuals as license holders and cannot be unambiguously matched to corporate records.

Table 1 summarizes the sample selection criteria and the number of restaurants matched to Florida corporate records. We exclude from the analysis restaurants matched to nonprofits and out-of-state firms.[13] We also exclude restaurants matched to firms registered for the first time after February 15, 2020.

2.3 Racial and Hispanic identity of potential borrowers

We classify firms based on the racial or Hispanic identity of the first officer or director listed in the firm's corporate record. For brevity we refer to this individual as the owner although it is possible that this individual manages the firm without having any ownership.

[11] In the robustness analyses in Table 13, we use an algorithm to identify affiliated firms and find larger disparities in the take-up of bank PPP loans, when we measure take-up across all of the restaurant's affiliates.

[12] http://www.myfloridalicense.com/DBPR/hotels-restaurants/lodging-public-records/

[13] A firm that is registered in another state but has a Florida mailing address would not be excluded by the earlier screen meant to exclude license holders with out-of-state mailing addresses.

Table 1
Restaurant Sample Selection Criteria

This table summarizes the sample selection criteria and the number of restaurants matched to Florida corporate records at different steps in the algorithm. Details of the matching algorithm are described in the Appendix.

Step	N **affected**	N **remaining**
0. Restaurants with seating		43,762
1. Drop out-of-state license holders	5,781	37,981
2. Drop licenses approved after February 15, 2020	3,138	34,843
3. Drop hotel restaurants	3,221	31,622
4. Drop franchise restaurants	5,767	25,855
5. Drop restaurants operated by municipalities and JVs	101	25,754
6. Drop unmatched restaurants	2,218	23,536
7. Drop firms incorporated after February 15, 2020	502	23,034
8. Drop non-profit and out-of-state firms	1,509	21,525

Howell, Kuchler, and Stroebel (2021) use a machine learning algorithm to estimate the probability of a racial or Hispanic identity based on the officer's name and the location of the business. Regression results that use estimated probabilities must be interpreted with caution because they may either overstate or understate the effect of racial or Hispanic identity, depending on the relative accuracy with which the algorithm can classify different groups. As a simple example, consider a sample that consists of non-Hispanic white and Black individuals. Suppose first that conditional on being a white person, the algorithm always correctly classifies the person's race as white, but that conditional on being a Black person, the algorithm assigns a 50% probability of being a Black person. In this example, the estimated coefficient on the probability of being Black will be twice as large as the true effect of being Black. If on the other hand, the algorithm correctly identifies Black people as Black but assigns positive probability of being Black to white people, then the estimated coefficient on the probability of being Black will be smaller than the true effect. The direction and magnitude of the bias will depend on the relative accuracy with which the algorithm can classify different groups and potentially their correlation with other firm characteristics. Note that the common intuition that measurement error in the explanatory variable biases the estimated coefficient towards zero does not apply in this setting because the distribution of measurement error is not symmetric.

In addition to the unknown bias in the estimates of the direct effect of race and Hispanic identity, measurement error of this designation may be correlated with firm characteristics and may therefore affect the coefficients of any interaction terms.[14] Suppose, for example, we

[14] Fryer and Levitt (2008) show that adoption of distinctly Black names varies over time and is strongly correlated with socioeconomic status. This means that inferred race may capture the effects of age and socioeconomic status.

Table 2
Match to Voter Registration Data

This table summarizes the match between restaurant owners and voter registration data. Details of the matching algorithm are described in the Appendix.

Step	*N*	**%**
0. Restaurants matched to corporate records	21,525	100.0%
1. First officer is a firm or out-of-state	1,169	5.4%
2. Unique match within county	10,096	46.9%
3. Tie broken using address	836	3.9%
4. All matches agree on race	555	2.6%
5. Multiple potential matches	1,427	6.6%
6. No matches	7,442	34.5%

wanted to know whether disparities are attenuated for Black-owned firms with existing bank relationships. If Black-owned businesses are less likely to have existing bank relationships, then measures of bank relationships may provide incremental information about whether the business owner is Black relative to the output of a name-based algorithm. The interaction term will then reflect both the effect of bank relationships and relative measurement error in race.

To overcome the limitations of name-based algorithms, we take advantage of Florida voter registration data, which report each registered voter's self-identified racial or Hispanic identity.[15] Voter registrants can specify whether they identify as one of the following: 1) American Indian or Alaskan Native, 2) Asian or Pacific Islander, 3) Black, not Hispanic, 4) Hispanic, 5) white, not Hispanic, 6) other, or 7) multi-racial. Because of the small number of observations, we combine American Indian or Alaska Native and multi-racial in the other category. For brevity, we refer to "Asian or Pacific Islander" as Asian and to "Black, not Hispanic" as Black, and "white, not Hispanic" as white. Note that while these classifications are imperfect, Ganong et al. (2020) show that there is a 99% agreement rate between the way voters identify themselves in a sample of voter registration files and mortgage applications.

We match the firm's owner to voter registration data based on name and location. Details of the matching algorithm are provided in the Appendix. Overall, we are able to identify a restaurant owner's racial or Hispanic identity for 56% of the sample restaurants. In most of these cases, we have a unique match within a county. If there are multiple potential matches, but they all report the same racial or Hispanic identity, we use what is reported even though we cannot identify the specific voter match.

[15] https://dos.myflorida.com/elections/data-statistics/voter-registration-statistics/voter-extract-disk-request/

One further advantage of using voter registration data is that by conditioning on the owner being a registered voter, we exclude restaurants that may have been ineligible for PPP funding.[16] The downside is that the sample of registered voters may not be representative of the population of restaurant owners. In particular, registered voters may be more aware of government interventions such as PPP and may be more likely to apply.

2.4 Lenders

To classify PPP lenders as either banks or nonbanks we first match lenders based on name and location to the database on financial institutions maintained by the Federal Financial Institutions Examination Council's National Information Center (NIC). Unmatched lenders and lenders classified by NIC as domestic entity other (DEO) are classified as nonbanks. We also classify Cross River Bank, Celtic Bank Corp, and WebBank as nonbanks because they hold loans originated by online fintech lenders and do not originate their own PPP loans. The list of nonbank lenders is reported in the Appendix Table A2.

2.5 Bank relationships

We measure existing bank relationships of restaurants in our data using Uniform Commercial Code (UCC) filings. Lenders file UCC financing statements to establish priority in the collateral pledged to them. Using Florida UCC filings data[17], we match debtors to Florida corporate records. We match lenders to the National Information Center (NIC) and Capital IQ, and classify them as bank or nonbank. For each restaurant in our sample, we then check whether the firm had an active UCC filing and whether the underlying loan was with a bank or a nonbank.

2.6 Summary statistics

Table 3 reports summary statistics for the voter registration sample and for the full sample. In the full sample, race and Hispanic identity variables are probabilities estimated

[16] While the CARES Act does not disqualify foreign-owned businesses from receiving PPP loans, the SBA did not provide explicit guidance, thereby sowing confusion among lenders and causing some lenders to deny applications by non-citizens. One of the changes implemented by President Biden on February 22, 2021 was to require SBA to provide clear guidance that otherwise eligible businesses cannot be denied access.

[17] https://www.floridaucc.com/uccweb/ucc.aspx

by the open-source `ethnicolr` model built using Florida voter registration data.[18]. *Other* and *Female* variables are available only within the voter registration sample. The voter registration sample has a lower share of Black (4% vs. 8%), Hispanic (17% vs. 20%) and Asian owners (10% vs. 17%) than the full sample. Some of these differences are due to the name-based algorithm assigning to white owners positive probability of being minority owners. Otherwise, firms in the voter registration sample are similar to firms in the full sample in terms of restaurant size, firm age, and having secured loans with banks and nonbanks.

Table 3
Summary Statistics

This table reports summary statistics for Florida restaurants matched to voter registration data versus the full sample of restaurants matched to Florida corporate records and having an individual first officer. The sample consists of restaurants with seating that were licensed before February 15, 2020, whose license holders are Florida for-profit firms registered before February 15, 2020, and whose owner's race can be identified using Florida voter registration data. Hotel and franchise restaurants are excluded. *Female* and *Other* are available only within the voter registration sample.

	Voter registration ($N = 10,888$)				Full sample ($N = 20,356$)			
	Mean	SD	25th	75th	Mean	SD	25th	75th
Black	0.04	0.20	0.00	0.00	0.08	0.16	0.01	0.07
Hispanic	0.17	0.38	0.00	0.00	0.20	0.32	0.01	0.20
Asian	0.10	0.30	0.00	0.00	0.17	0.34	0.00	0.04
Other	0.04	0.20	0.00	0.00				
Female	0.28	0.45	0.00	1.00				
Number of seats	89.63	104.34	35.00	140.00	87.60	97.56	30.00	130.00
Firm age	10.23	9.76	3.27	14.21	9.36	9.51	2.90	12.72
Bank UCC	0.17	0.38	0.00	0.00	0.15	0.36	0.00	0.00
Nonbank UCC	0.14	0.35	0.00	0.00	0.14	0.35	0.00	0.00
EIDL	0.36	0.48	0.00	1.00	0.33	0.47	0.00	1.00
PPP (2020)	0.70	0.46	0.00	1.00	0.66	0.47	0.00	1.00
Bank PPP (2020)	0.64	0.48	0.00	1.00	0.59	0.49	0.00	1.00
Nonbank PPP (2020)	0.06	0.24	0.00	0.00	0.07	0.26	0.00	0.00
PPP (2021)	0.47	0.50	0.00	1.00	0.44	0.50	0.00	1.00
Bank PPP (2021)	0.42	0.49	0.00	1.00	0.39	0.49	0.00	1.00
Nonbank PPP (2021)	0.05	0.21	0.00	0.00	0.05	0.22	0.00	0.00

Of the firms in the the voter registration sample, 70% receive PPP loans in 2020, whereas 66% receive PPP loans in the full sample of restaurants. A large percentage of these loans are originated by banks in both samples. 64% of firms received a PPP loan from a bank in the voter registration sample as compared to 59% in the full sample.

[18] https://github.com/appeler/ethnicolr

3 Documenting Disparities

We begin by reporting in Table 4 the distribution of outcomes and firm characteristics for restaurants owned by different demographic groups. Out of white-owned restaurants, 74% received a PPP loan. Almost all of these were from a bank. A third of white-owned restaurants received an EIDL loan, with most recipients also receiving a PPP loan. Only 5% of white-owned restaurants received an EIDL loan without also receiving a PPP loan.

The picture is very different for Black-owned restaurants. Less than a half (47%) received a PPP loan. Conditional on receiving a PPP loan, almost 28% of PPP loans were from a nonbank. Three times as many Black- as white-owned restaurants received an EIDL loan without also receiving a PPP loan. Furthermore, 38% of Black-owned restaurants did not receive any COVID-19 emergency loan.

Table 4
Utilization of Emergency Loans by Different Groups

This table reports the share of restaurants owned by different groups that received different types of COVID-19 emergency loans. Population and median household income are in thousands. The sample consists of restaurants with seating that were licensed before February 15, 2020, whose license holders are Florida for-profit firms registered before February 15, 2020, and whose owner's race can be identified using Florida voter registration data. Hotel and franchise restaurants are excluded.

	Race/Ethnicity					Gender	
	White	Black	Asian	Hispanic	Other	Male	Female
Outcomes							
Received PPP	0.74	0.47	0.71	0.63	0.69	0.72	0.66
Bank	0.69	0.34	0.58	0.57	0.60	0.66	0.58
Nonbank	0.05	0.13	0.13	0.06	0.09	0.06	0.08
Received EIDL	0.33	0.37	0.38	0.42	0.40	0.36	0.35
EIDL and PPP	0.29	0.22	0.31	0.32	0.32	0.30	0.27
EIDL, but not PPP	0.05	0.15	0.06	0.11	0.08	0.06	0.08
No loan	0.22	0.38	0.23	0.26	0.22	0.22	0.26
Firm characteristics							
Firm age	11.25	6.68	7.90	8.90	9.24	10.40	9.79
Num. seats	100.99	52.65	68.13	76.08	80.77	97.09	74.12
Bank UCC	0.21	0.07	0.09	0.11	0.15	0.19	0.12
Nonbank UCC	0.15	0.14	0.08	0.14	0.12	0.15	0.12
ZIP code characteristics							
Population (000)	27.28	37.57	34.10	37.21	31.92	30.18	30.54
White population share	0.81	0.55	0.76	0.77	0.74	0.79	0.78
Num. bank branches	9.55	7.05	10.61	10.62	9.29	9.85	9.38
Median household income (000)	61.77	49.48	62.12	56.52	58.63	60.86	58.66

For the other demographic groups we consider, the pattern of outcomes is generally in between the ones for white and Black restaurant owners. Other minority-owned restaurants are less likely to receive bank PPP loans, more likely to receive nonbank PPP loans, more

likely to receive EIDL loans without also receiving PPP loans, and more likely to receive no emergency loans at all.

Table 4 also reports firm and ZIP code characteristics for restaurants owned by different demographic groups. Minority-owned restaurants and restaurants owned by women tend to be younger and smaller. They are also less likely to have an existing secured loan with either a bank or nonbank lender. For example, relative to white-owned restaurants, Black-owned restaurants are only one third as likely to have a secured loan with a bank (7% vs. 21%).

Minority-owned restaurants tend to be located in ZIP codes with larger populations and lower white population share. Black-owned restaurants, for example, are located in ZIP codes in which white people account for 55% of the overall population. In contrast, white-owned restaurants are located in ZIP codes in which white people account for 81% of the overall population. Black-owned restaurants are also located in ZIP codes with fewer bank branches and lower median household income. Our regressions specifications will account for these geographic differences by comparing white- and minority-owned restaurants located in the same ZIP code.

Table 5 reports the results of linear probability model regressions of receiving different types of emergency loans on dummy variables for minority- and female-owned restaurants. The unit of observation is a restaurant r located in ZIP code z and owned by firm f. A given firm can own multiple restaurants. Table 13 shows the robustness of our results to analyzing single-restaurant firms, which account for more than 90% of our sample.

In columns 1–3 of Table 5 the dependent variable is equal to one if the restaurant received a PPP loan and zero otherwise. We include racial, Hispanic and female restaurant-owner dummies, except for white restaurant owners, so we are measuring the likelihood of different demographic groups getting a PPP loan relative to restaurants owned by white males. As shown in the first column, Black-owned restaurants are 26.2% less likely than white-owned restaurants to receive a PPP loan, while Hispanic-owned restaurants are 10.1% less likely. Both coefficients are statistically significant. Asian-owned restaurants are only slightly less likely to receive a PPP loan, while restaurants owned by women are 4.9% less likely to receive a PPP loan.

One reason why minority-owned restaurants are less likely to receive PPP loans is that they may be located in under-served banking markets (Wang and Zhang, 2020). The second column of Table 5 adds ZIP code fixed effects so that the regression specifications compare white- and minority-owned restaurants located in the same ZIP code. The estimated effects decline modestly but remain both economically and statistically significant. For example,

Table 5
Racial Disparities in the Utilization of Emergency Loans

This table reports the results of linear probability model regressions of receiving different types of emergency loans on restaurant owner's race:

$$Emergency\ loan_{f,r,z} = \alpha_z + \beta \cdot Minority_f + \delta \cdot Female_f + \gamma' X_{f,r} + \varepsilon_{f,r,z},$$

where f indexes firms, r indexes restaurants and z indexes ZIP codes. The sample consists of restaurants with seating that were licensed before February 15, 2020, whose license holders are Florida for-profit firms registered before February 15, 2020, and whose owner's race can be identified using Florida voter registration data. Hotel and franchise restaurants are excluded. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. $N = 10,888$.

	PPP			Bank PPP			Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Black	−0.262***	−0.205***	−0.145***	−0.337***	−0.268***	−0.199***	0.076***	0.064***	0.055***	0.042*	0.039	0.036
	(0.024)	(0.028)	(0.027)	(0.023)	(0.027)	(0.026)	(0.016)	(0.017)	(0.018)	(0.024)	(0.027)	(0.027)
Hispanic	−0.101***	−0.070***	−0.049***	−0.108***	−0.072***	−0.048***	0.007	0.003	−0.000	0.092***	0.052***	0.048***
	(0.012)	(0.015)	(0.015)	(0.013)	(0.015)	(0.015)	(0.006)	(0.007)	(0.007)	(0.013)	(0.015)	(0.015)
Asian	−0.017	−0.010	0.024	−0.101***	−0.092***	−0.053***	0.082***	0.080***	0.076***	0.048***	0.033*	0.031*
	(0.015)	(0.016)	(0.015)	(0.016)	(0.017)	(0.017)	(0.011)	(0.011)	(0.011)	(0.016)	(0.017)	(0.017)
Other	−0.042*	−0.026	−0.005	−0.079***	−0.057**	−0.034	0.037***	0.032**	0.029**	0.068***	0.055**	0.054**
	(0.023)	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)	(0.014)	(0.014)	(0.014)	(0.024)	(0.025)	(0.025)
Female	−0.049***	−0.040***	−0.023**	−0.063***	−0.053***	−0.034***	0.015***	0.014**	0.012**	−0.023**	−0.012	−0.009
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.005)	(0.006)	(0.006)	(0.010)	(0.011)	(0.011)
Ln(Seats)			0.066***			0.074***			−0.008***			0.010**
			(0.005)			(0.005)			(0.003)			(0.005)
Ln(Firm age)			0.033***			0.039***			−0.006**			−0.021***
			(0.005)			(0.005)			(0.002)			(0.005)
R^2	0.021	0.117	0.141	0.031	0.129	0.157	0.014	0.100	0.101	0.006	0.094	0.096
ZIP FEs		✓	✓		✓	✓		✓	✓		✓	✓

Black-owned restaurants within the same ZIP code of white-owned restaurants are 20.5% less likely to receive PPP loans. For Hispanic-owned restaurants the difference is 7.0% and for restaurants owned by women the difference is 4.0%. Thus, disparities in PPP utilization do not stem solely from characteristics of an area—such as low bank branch density—that make access to PPP loans more difficult or make them less desired by restaurant owners. In fact, location explains only about a quarter of the difference between the PPP utilization of Black- and white-owned restaurants.

In column 3, we add controls for firm age and size, using the log number of restaurant seats as a proxy for size. Larger and older restaurants are significantly more likely to receive PPP loans. Controlling for firm characteristics further reduces the magnitude of the coefficients on minority- and female-owned restaurants. Black-owned restaurants are 14.5% less likely to receive PPP funding once we add location, size and age to the regressions. Relative to the regression with no controls, the estimated disparities are cut by about half. Still the coefficients remain economically and statistically significant.

Next, we estimate separate regressions for bank and nonbank PPP lenders, with bank results reported in columns 4–6 and nonbank results reported in columns 7–9. The findings indicate that the lower rate of PPP borrowing by minority- and female-owned restaurants is driven by the lending behavior of banks. For example, as shown in column 4, Black-owned restaurants are 33.7% less likely than white-owned restaurants to receive PPP funding from a bank. Adding ZIP code fixed effects in column 5 and then restaurant characteristics in column 6 reduces the magnitude of the effect, but it remains large and statistically significant. Black-owned restaurants are 19.9% less likely to get PPP funding from a bank. For Hispanic-owned restaurants, the difference is 4.8%, for Asian-owned restaurants it is 5.3%, and for female-owned restaurants it is 3.4%. All of these differences are statistically significant, and all of them are greater than the estimated differences for all PPP loans reported in columns 1–3.

In columns 7–9 we report the results for nonbank PPP loans. The regressions indicate that nonbanks tend to offset the lower rate of bank PPP lending to minority-owned restaurants, particularly in the case of restaurants with Black and Asian owners. The regression results reported in column 9, which include ZIP code fixed effects and restaurant characteristics, indicate that Black-owned restaurants are 5.5% more likely to receive a nonbank PPP loan and Asian-owned restaurants are 7.6% more likely to receive a nonbank PPP loan. Female-owned restaurants are 1.2% more likely to receive a nonbank PPP loan. The estimated effect for Hispanic-owned restaurants is small and statistically insignificant. The higher take-up rate of nonbank PPP loans by minority-owned restaurants suggests that these

businesses substitute away from banks because they find it more difficult or less desirable to access PPP loans from banks. This finding cuts against the idea that the lower overall take-up rate of PPP loans by minority-owned restaurants documented in columns 1–3 is due to lower demand for emergency loans by these businesses.

In columns 10–12, we present results on the likelihood of receiving an EIDL loan. As noted above, firms apply for EIDL loans directly through the SBA website. They can apply for and receive loans from both PPP and EIDL at the same time, though the proceeds must be used for different purposes. In the column 10 regression, which does not control for location or firm characteristics, Black-, Hispanic-, and Asian-owned restaurants are 4.2%, 9.2%, and 4.8% more likely than white-owned restaurants to receive loans from EIDL. The coefficient on female is a statistically significant -2.3%. Controlling for location and firm characteristics in columns 11 and 12 reduces the magnitude and statistical significance of the coefficients.

Note that in the nonbank PPP regression the effects of restaurant size and age are small and negative, while in the EIDL loan regression the effect of age is negative and the effect of size is small and positive. These effects are in contrast to those in the bank PPP regressions in which the effects of size and age are positive and larger in magnitude. The different effects across the regressions suggests that these restaurant characteristics are unlikely to proxy for loan demand because in that case we would expect the coefficients in both regressions to have the same sign and similar magnitude. Rather, the findings suggest that restaurant size and age proxy for bank loan supply. This could be because banks find it more attractive to make PPP loans to larger and older restaurants, or because it is more likely that larger and older restaurants have pre-existing bank relationships that banks prioritize in making PPP loans. It is also possible that smaller, less established restaurants are less likely to apply to banks because they do not have the resources to manage a more complex and onerous process than that offered by nonbanks and the EIDL program.

The fact that minority-owned restaurants apply for emergency loans from nonbanks and the EIDL program suggests that lower demand for emergency loans does not explain the racial disparities in bank PPP lending. To control more directly for demand we can limit the sample to firms that received any type of emergency loan. Within this sample of firms with demand for emergency loans, we can ask whether minority- and female-owned firms were less likely to receive bank PPP loans.

In Table 6, we find that the results go through within this subsample of firms that received some type of emergency loan. Minority- and female-owned restaurants are less

Table 6
Demand for Credit

This table reports the results of linear probability model regressions of receiving a bank PPP loan on the restaurant owner's race, limiting the sample to firms that receive any type of emergency loans:

$$Bank\ PPP_{f,r,z} = \alpha_z + \beta \cdot Minority_f + \delta \cdot Female_f + \gamma' X_{f,r} + \varepsilon_{f,r,z},$$

where f indexes firms, r indexes restaurants, and z indexes ZIP codes. The sample consists of restaurants that receive either PPP or EIDL loan. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)
Black	−0.320***	−0.266***	−0.267***	−0.222***
	(0.030)	(0.033)	(0.030)	(0.033)
Hispanic	−0.100***	−0.078***	−0.081***	−0.068***
	(0.012)	(0.014)	(0.012)	(0.014)
Asian	−0.124***	−0.119***	−0.097***	−0.095***
	(0.016)	(0.016)	(0.016)	(0.016)
Other	−0.091***	−0.075***	−0.071***	−0.060***
	(0.023)	(0.023)	(0.023)	(0.023)
Female	−0.046***	−0.044***	−0.031***	−0.030***
	(0.010)	(0.010)	(0.010)	(0.010)
Ln(Seats)			0.057***	0.053***
			(0.004)	(0.005)
Ln(Firm age)			0.028***	0.031***
			(0.004)	(0.005)
N	8,348	8,348	8,348	8,348
R^2	0.041	0.156	0.069	0.180
ZIP FEs		✓		✓

likely to receive bank PPP loans.

It is also worth noting that the coefficients on the number of seats and firm age decrease from 0.074 and 0.039 in column 6 of Table 5 to 0.053 and 0.031 in column 3 of Table 6. This suggests that about 20–30% of the magnitude of these coefficients captures demand for emergency loans, the rest is likely to capture supply-side factors.

Overall, the results in Table 5 indicate that minority-owned restaurants are significantly less likely to receive bank PPP loans but are more likely to receive nonbank PPP loans and EIDL loans. Furthermore, firm characteristics have greater explanatory power for bank PPP loans than for nonbank PPP loans and EIDL loans. These results suggest that the lower take-up rate of bank PPP loans by minority-owned restaurants is unlikely to be due to lower demand for emergency loans, but rather due to aspects of the loan origination process at banks that disadvantage minority restaurant-owners and women.

4 Bank Relationships

In this section we explore the role that bank relationships could play in explaining racial disparities in PPP lending. If banks prioritize businesses with which they have strong relationships, and minority-owned businesses have relatively weak relationships with banks, then we would expect to see racial disparities in bank PPP lending without adequate controls for these relationships. Numerous studies have shown that Black- and Hispanic-owned businesses are more likely to be turned down for loans, controlling for credit quality and personal wealth, and less likely to apply for loans (Blanchflower, Levine, and Zimmerman, 2003; Cavalluzzo and Wolken, 2005). In addition, minority-owned businesses report greater dissatisfaction with their financial services providers (Federal Reserve Banks, 2021). This evidence suggests that, relative to white-owned restaurants, minority-owned restaurants are likely have weaker relationships with banks.

While we do not observe the full extent of a restaurant's banking relationships, it is likely that almost all of the restaurants in the sample have some kind of banking relationship since they must have a bank account to receive credit card payments.[19] Nevertheless, some may have stronger bank relationships than others because they use a wider variety of banking services or because they have been bank customers for a longer time. To get at the strength of a firm's relationship with a bank, we collect data on whether they have a bank loan outstanding. Although we cannot observe all of a firm's loans, we can observe their secured loans except those that are secured by real estate. According to Luck and Santos (2021), out of all loans to firms with less than $50 million in assets by banks that have been subject to the Federal Reserve's stress tests, only 3.6% are unsecured and 22% are secured by real estate. Furthermore, Blanchflower, Levine, and Zimmerman (2003) show that Black-owned firms utilize credit cards as a form of debt at the same rate as white-owned firms. Thus, it is likely that by observing non-mortgage secured loans we are observing the most meaningful cross-sectional variation in a firm's borrowing.

As noted in the data section, we use Florida UCC financing statements to measure secured borrowing relationships between restaurants and their lenders, both bank and nonbank. These financing statements are filed by lenders to assert their security interest in a loan. The security interest could be in physical capital such as equipment or could be a general lien on the business. We consider a restaurant to have a secured borrowing relationship with a lender if there was an active UCC filing by that lender as of January 1, 2020. As shown

[19] A review of 100 restaurants, both Black-owned and white-owned, indicates that almost all of them accept credit card payments.

in Table 4, the percentage of minority-owned restaurants that have UCC loans with banks is considerably lower than it is for white-owned restaurants, although the percentages are quite similar for loans from nonbanks.

The dependent variable in the first three columns of Table 7 is whether the restaurant receives a bank PPP loan. In columns 4–6 we present regressions for nonbank PPP loans and in columns 7–9 we present results for EIDL loans. The first column in each block of regressions (bank, nonbank, EIDL) repeats the baseline specifications from columns 6, 9, and 12 in Table 5, while the other columns add controls for whether the firm has an active bank or nonbank UCC loan and interaction terms described below.

The results reported in column 2 indicate that having a bank UCC loan is associated with a 9.3% higher probability of receiving a bank PPP loan. The effect of having a nonbank UCC loan is considerably smaller though a still sizable and statistically significant 4.8%. These effects are fairly large. Given that only 36% of restaurants do not receive bank PPP loans, a 9.3% increase in the probability of receiving a bank PPP loan reduces this probability by about 25%.

Controlling for secured lending relationships tends to reduce the coefficient estimates of some of the minority restaurant-owner dummies, but disparities remain. The strongest effect is on the coefficient of *Asian*: its magnitude is reduced by 18% from -5.3% to -4.4%. The coefficient on *Black* is essentially unchanged. Black-owned restaurants are still almost 20% less likely than white-owned restaurants to receive a bank PPP loan even after controlling for existing UCC loans. The estimated effects on the coefficients of the minority dummies are generally smaller than what one would expect if prior UCC loans had the same effect on bank PPP borrowing for all demographic groups. In this case, we would expect the coefficient on the minority restaurant-owner dummies to fall by roughly 9.3% (the effect of bank UCC loans on bank PPP loans) times the difference in the fraction of white-owned restaurants that have bank UCC loans and the fraction of the minority-owned restaurants that have bank UCC loans. For example, Hispanic-owned restaurants are 10% less likely to have a bank UCC loan than white-owned restaurants. Thus, we would expect the coefficient of *Hispanic* to fall by 0.9%; in fact, it falls by only 0.5%.

Why doesn't controlling for secured lending relationships have a bigger effect on estimated disparities? One possibility is that minority-owned restaurants have relationships with banks that were less active PPP lenders, and thus had to find other banks from which to receive PPP loans. To examine this possibility, we look at the PPP lending intensity of banks having secured lending relationships with white- versus minority-owned restaurants. We include all

Table 7
UCC Lending Relationships

This table reports the results of linear probability model regressions of receiving different types of emergency loans on the restaurant owner's race and controls for existing UCC lending relationships:

$$Emergency\ loan_{f,r,z} = \alpha_z + \beta \cdot Minority_f + \delta \cdot Female_f + \theta \cdot UCC\ Loan_f + \gamma' X_{f,r} + \varepsilon_{f,r,z},$$

where f indexes firms, r indexes restaurants, and z indexes ZIP codes. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. $N = 10,888$.

	Bank PPP			Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black	−0.199***	−0.198***	−0.176***	0.055***	0.053***	0.059***	0.036	0.033	0.025
	(0.026)	(0.026)	(0.029)	(0.018)	(0.018)	(0.020)	(0.027)	(0.027)	(0.029)
Hispanic	−0.048***	−0.043***	−0.052***	−0.000	−0.002	−0.004	0.048***	0.051***	0.047***
	(0.015)	(0.015)	(0.017)	(0.007)	(0.007)	(0.008)	(0.015)	(0.015)	(0.017)
Asian	−0.053***	−0.044***	−0.049***	0.076***	0.075***	0.077***	0.031*	0.039**	0.025
	(0.017)	(0.017)	(0.018)	(0.011)	(0.011)	(0.012)	(0.017)	(0.017)	(0.018)
Other	−0.034	−0.030	−0.037	0.029**	0.029**	0.035**	0.054**	0.057**	0.049*
	(0.025)	(0.025)	(0.028)	(0.014)	(0.014)	(0.017)	(0.025)	(0.025)	(0.029)
Female	−0.034***	−0.029***	−0.032***	0.012**	0.011*	0.007	−0.009	−0.006	−0.004
	(0.011)	(0.011)	(0.012)	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)	(0.012)
Ln(Seats)	0.074***	0.067***	0.079***	−0.008***	−0.008***	−0.006**	0.010**	0.003	0.007
	(0.005)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)
Ln(Firm age)	0.039***	0.033***	0.040***	−0.006**	−0.005**	−0.004	−0.021***	−0.025***	−0.019***
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)	(0.005)
Bank UCC loan		0.093***	0.119***		−0.027***	−0.035***		0.053***	0.038**
		(0.012)	(0.016)		(0.006)	(0.007)		(0.013)	(0.018)
Nonbank UCC loan		0.048***	0.053***		0.027***	0.038***		0.098***	0.133***
		(0.013)	(0.018)		(0.008)	(0.011)		(0.014)	(0.020)
Black× Bank UCC loan			−0.224**			0.090			0.220**
			(0.091)			(0.065)			(0.103)
Ln(Seats)× Bank UCC loan			−0.068***			0.004			−0.018
			(0.012)			(0.005)			(0.014)
Ln(Firm age)× Bank UCC loan			−0.034***			−0.004			−0.036**
			(0.013)			(0.006)			(0.015)
Black× Nonbank UCC loan			−0.008			−0.098**			−0.073
			(0.074)			(0.042)			(0.078)
Ln(Seats)× Nonbank UCC loan			−0.015			−0.015*			−0.011
			(0.014)			(0.008)			(0.015)
Ln(Firm age)× Nonbank UCC loan			−0.039**			−0.009			−0.026
			(0.016)			(0.009)			(0.018)
R^2	0.157	0.164	0.169	0.101	0.104	0.106	0.096	0.103	0.106
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓

Florida-based firms that had an active UCC lending relationship with a bank as of January 1, 2020. We define a bank's PPP lending intensity as the number of PPP loans extended to Florida firms divided by the number of UCC loans extended to Florida firms. The average PPP lending intensity of banks from which white-owned restaurants have secured loans is 2.33 while its is 2.34 for banks from which Black-owned restaurants have secured loans. The difference is not statistically significant.

Another possible explanation for why including secured lending in the regression has limited effect on disparities is that prior bank borrowing relationships are weaker for minority-owned restaurants and thus banks are less likely to prioritize them in the PPP lending process. A related explanation is that minority business owners are more dissatisfied than white business owners with their bank borrowing relationships and, as a result, are less likely to apply for a bank PPP loan.

We examine these explanations in column 3 by including interaction terms between the bank UCC loan variable and the minority restaurant-owner dummies. (Except for Black-owned restaurants we do not report the interactions with minority dummies in Table 7. These estimates are available in the Appendix Table A3.) We also include interactions between the bank UCC loan dummy and restaurant characteristics given that restaurant characteristics vary by racial and Hispanic identity, and may independently affect whether prior bank borrowing is related to bank PPP loan access. The estimated coefficients of the bank UCC loan variable and the minority restaurant-owner dummies are small and statistically insignificant except for the interaction with *Black*, which is large, negative and statistically significant. The coefficient implies that the effect of prior bank borrowing on bank PPP borrowing is 22.4% less for Black-owned restaurants than for white-owned restaurants. Given that white-owned restaurants with outstanding bank loans are 11.9% more likely than those without them to get bank PPP funding, the point estimates imply that Black-owned restaurants with outstanding bank loans are actually 10.5% less likely than those without them to get bank PPP loans, although this effect is statistically insignificant. Nevertheless, what we can conclude is that bank borrowing relationships are less valuable for Black-owned restaurants in accessing PPP loans from banks. This could be either because banks are less likely to prioritize their Black-owned business customers or because Black business owners are more dissatisfied with their bank relationships and thus less willing to apply to the bank for a PPP loan.

Columns 4–6 report the results for nonbank PPP loans. The coefficient on bank UCC loans in column 4 is -2.7% while the coefficient on nonbank UCC loan is 2.7%. Given that a prior bank relationship predicts an increased likelihood of getting a bank PPP loan, it is not

surprising that it reduces the probability of getting a nonbank PPP loan. The coefficients of the interactions terms are reported in column 6. Here we see that the interaction of *Black* with nonbank UCC loan is negative and statistically significant, indicating that a history of borrowing from nonbanks is less helpful to Black-owned restaurants in securing a nonbank PPP loan. There are two possible explanations of this finding. One is that nonbank borrowing relationships are weaker for Black-owned businesses, just as we argued may be the case for bank borrowing relationships. Another possibility is that compared to white-owned businesses that receive nonbank UCC loans, Black-owned businesses are less likely to receive nonbank UCC loans from lenders that participate in the PPP program. For example, Black-owned businesses may be more likely to borrow from equipment finance companies or merchant cash advance lenders, which are presumably less likely to participate in PPP relative to fintech lenders.

Columns 7–9 examine the effect of lending relationships on EIDL loans. In column 8 the coefficients on bank and nonbank UCC loans are positive and highly statistically significant. Since firms apply for EIDL loans directly to the SBA, the UCC lending relationship variables in this regression are likely to capture demand for credit as EIDL loans are meant to allow firms to make payments on their existing debt.

Taken together, these findings indicate that differences in bank borrowing relationships between white- and minority-owned businesses do not explain disparities in bank PPP take-up rates. Indeed, the results suggest that for Black-owned businesses these relationships are not helpful in procuring bank PPP loans. While we cannot pinpoint a reason why, it is possible that banks are less likely to prioritize their Black-owned business customers. It is also possible that Black business owners are more dissatisfied with their bank lender and thus less likely to apply for a bank PPP loan. We next explore what role racial bias may play in explaining racial disparities in bank PPP lending.

5 Racial Bias

In this section, we look at the effect of racial bias on bank PPP lending. Specifically, we ask whether minority-owned restaurants are less likely to receive bank PPP loans in areas with stronger racial bias. We use data on explicit and implicit racial bias collected by Project Implicit[20]. Project Implicit offers a number of online implicit association tests

[20] https://osf.io/y9hiq/

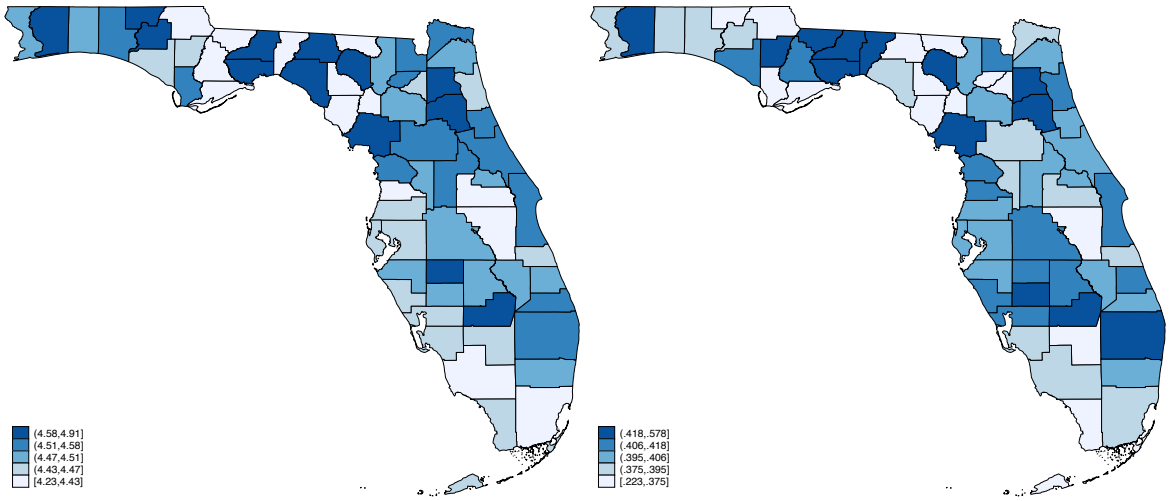
that test-takers anywhere in the world can take to measure their implicit social attitudes. We use the results of the Race test, also known as the Black/White test, which measures implicit preference for white over Black people.[21] The test also asks subjects about their explicit preferences on a seven-point scale, where 1 is "I strongly prefer African Americans to European Americans", 4 is "I like European Americans and African Americans equally", and 7 is "I strongly prefer European Americans to African Americans."

Implicit bias has been shown to be associated with discriminatory behavior. Glover, Pallais, and Pariente (2017) show that implicit bias of grocery store managers affects the performance of minority cashiers. On days when they are supervised by biased managers, minority cashiers are more likely to be absent from work and take longer to scan items and check out customers. Hehman, Flake, and Calanchini (2018) show that local implicit racial bias is associated with disproportionate use of lethal force against Black people.

We calculate the county-level average across white respondents taking the test between 2008–2019. The median county has 347 valid responses. Glades county has the fewest responses at 14. Figure 1 plots county-level averages of explicit and implicit bias. Larger values and darker colors indicate stronger bias. The correlation between explicit and implicit bias across all counties is 0.33. The correlation almost doubles to 0.58 when we limit the sample to the 42 counties with at least 100 responses.

Table 8 reports the results of linear probability models for bank PPP loans, nonbank PPP loans, and EIDL loans. The main variables of interest are the minority restaurant-owner dummies and their interactions with county-level explicit and implicit bias. Odd-numbered columns report the results for explicit bias, while even-numbered columns report the results for implicit bias. Bias measures are standardized to a mean of zero and unit standard deviation so that the interaction coefficients capture the effect of a one standard deviation increase in racial bias. The direct effect of bias is absorbed by the ZIP code fixed effects included throughout. To account for the likelihood that bias in counties with few test takers is measured with more noise, observations are weighted by the number of responses in the county. Equal weighted regressions generate slightly weaker results. Standard errors are adjusted for clustering by county to match the level at which we measure the key explanatory variable.

[21] Project Implicit also offers test of implicit attitudes towards Asian Americans, which one could potentially use to ask whether businesses owned by Asian Americans are less likely to receive bank PPP loans in counties with stronger anti-Asian bias. The Asian Implicit Association Test has many fewer responses, however. Over the 2014–2019 period, during which a test-taker's county is included in the data, no results are available for 10 out of 67 Florida counties. The median county has only 17 responses by white test-takers.



(a) Explicit bias **(b)** Implicit bias

Figure 1. Explicit and implicit racial bias across Florida counties This figure reports county-level averages of explicit and implicit racial bias of white respondents to the Race Implicit Association Test. Larger values indicate stronger bias against African Americans. Explicit bias is measured on a scale from 1 to 7, with subjects explicitly stating whether they "strongly prefer African Americans to European Americans" (1) or they "strongly prefer European Americans to African Americans" (7). Implicit bias is the score on the implicit association test. Tests taken during 2008–2019 are included. The median county has 347 respondents.

In columns 1 and 2, we examine the effect of racial bias on probability of receiving a bank PPP loan. The interaction between *Bias* and *Black* is negative and statistically significant. The economic magnitude is very large. A one standard deviation increase in racial bias is associated with 19.1%–22.8% reduction in the probability that a Black-owned restaurant receives a bank PPP loan, depending on whether we use explicit or implicit bias. Given that Black-owned restaurants are 25.2% (17.5%) less likely get a bank PPP loan in a county with average explicit (implicit) bias, this implies that Black-owned restaurants are 44.3% (40.3%) less likely to receive bank PPP funding in counties with explicit (implicit) bias one standard deviation above the mean.[22] The interactions between racial bias and the other minority restaurant-owner dummies are also negative, but smaller in magnitude and generally not statistically significant. It makes sense that although bias against Black people may be correlated with bias against other minority groups, its strongest effect is on the probability that Black-owned restaurants receive bank PPP loans.

[22] The average bias across Florida counties is just slightly above the average across all other counties in the U.S., but the difference is not statistically significant. This suggests that the effect of racial bias is likely not unique to Florida.

Table 8
Racial Bias

This table reports the results of linear probability model regressions of receiving different types of emergency loans on the restaurant owner's race interacted with explicit and implicit racial bias against Black people:

$$Emergency\ loan_{c,f,r,z} = \alpha_z + \beta \cdot Minority_f + \delta \cdot Female_f + \theta \cdot Minority_f \times Racial\ bias_c + \gamma' X_{f,r} + \varepsilon_{f,c,r,z},$$

where c indexes counties, f indexes firms, r indexes restaurants, and z indexes ZIP codes. County-level averages of racial bias are standardized so that the interaction terms represent the effect of a one standard deviation increase in racial bias. Regressions are weighted by the number of white respondents to the Race Implicit Association Test during 2008–2019 period. Standard errors are adjusted for clustering by county. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. $N = 10,888$.

	Bank PPP		Nonbank PPP		EIDL	
	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.252***	−0.175***	0.099***	0.050**	0.039	0.008
	(0.042)	(0.021)	(0.022)	(0.024)	(0.037)	(0.023)
Hispanic	−0.035	−0.037*	−0.025***	−0.014***	0.068**	0.066***
	(0.022)	(0.019)	(0.005)	(0.003)	(0.030)	(0.016)
Asian	−0.064**	−0.046**	0.093***	0.061***	0.031	0.018
	(0.027)	(0.019)	(0.014)	(0.011)	(0.031)	(0.033)
Other	−0.078***	−0.027	0.010	0.033*	0.071**	0.049***
	(0.028)	(0.026)	(0.014)	(0.017)	(0.033)	(0.018)
Female	−0.042***	−0.038***	0.032***	0.016*	−0.007	−0.005
	(0.010)	(0.006)	(0.010)	(0.008)	(0.014)	(0.010)
Black × Bias	−0.191***	−0.228***	0.124**	0.149**	0.070	0.147**
	(0.068)	(0.070)	(0.048)	(0.073)	(0.070)	(0.071)
Hispanic × Bias	−0.003	−0.027	−0.025**	−0.030***	0.007	0.031
	(0.060)	(0.064)	(0.010)	(0.011)	(0.039)	(0.036)
Asian × Bias	−0.044	−0.026	0.077**	0.105**	0.030	0.042
	(0.047)	(0.081)	(0.030)	(0.045)	(0.085)	(0.102)
Other × Bias	−0.125	−0.163*	−0.059	−0.039	0.051	0.093
	(0.078)	(0.092)	(0.038)	(0.057)	(0.048)	(0.068)
Female × Bias	−0.010	−0.006	0.038***	0.041*	−0.005	−0.018
	(0.014)	(0.011)	(0.014)	(0.022)	(0.015)	(0.016)
Ln(Seats)	0.063***	0.063***	−0.008***	−0.008***	0.004	0.004
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)
Ln(Firm age)	0.033***	0.033***	−0.003	−0.003	−0.019***	−0.019***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.007)	(0.007)
Bank UCC loan	0.084***	0.084***	−0.029***	−0.029***	0.052***	0.052***
	(0.016)	(0.016)	(0.005)	(0.005)	(0.012)	(0.012)
Nonbank UCC loan	0.033**	0.032**	0.035***	0.036***	0.097***	0.098***
	(0.016)	(0.016)	(0.013)	(0.013)	(0.008)	(0.007)
R^2	0.150	0.150	0.097	0.096	0.092	0.092
ZIP FEs	✓	✓	✓	✓	✓	✓

In columns 3 and 4, we present results for nonbank PPP loans. Here the coefficient on the interaction between *Black* and *Bias* is positive .124–0.149 and statistically significant. The magnitude of the coefficient is about two thirds of its size in columns 1 and 2. These results suggest that Black-owned restaurants are more likely to substitute from bank to nonbank

PPP loans in counties with greater racial bias. We also find a positive and statistically significant coefficient on the interaction of *Asian* and *Bias*, but modestly negative coefficient on the interaction of *Hispanic* and *Bias*.

Finally in columns 5 and 6, the dependent variable is receipt of an EIDL loan. As with nonbank PPP loans, we find a positive interaction between *Black* and *Bias*, but only the interaction with implicit bias is statistically significant.

In non-tabulated results, we find that implicit bias against females is associated with lower utilization of bank PPP loans by female-owned restaurants.[23] These results provide further support for the idea that local implicit bias affects how minority applicants are treated when applying for bank PPP loans.

One may be concerned that racial bias is correlated with other county-level characteristics such as white population share, personal income, and unemployment, that may explain differences in take-up rates and drive the results in Table 8. Table 9 addresses this concern by adding interactions of *Black* with various county-level characteristics.

Columns 1–2 report the results for bank PPP loans. The interaction between *Black* and county population is positive and highly significant suggesting that disparity in access to bank PPP loans is mitigated in more populous counties. Nevertheless, the interaction between *Black* and racial bias retains its economic and statistical significance.

When we look at nonbank PPP loans in columns 3–4, we once again find evidence of substitution by Black-owned restaurants to nonbank PPP loans in counties with greater racial bias. The interactions of *Black* with other county characteristics are generally not statistically significant.

Finally, in columns in 5–6 the dependent variable is whether a restaurant received an EIDL loan. Here we find significant interactions between *Black* and county-level characteristics and a negative interaction between *Black* and racial bias, where this interaction term is positive in the Table 8 without interactions with county-level characteristics. These results may be due to multicollinearity. When we include one county characteristic at a time, only the interaction with unemployment is statistically significant (and positive). Furthermore, in all of these regressions the interaction between *Black* and racial bias is positive.

[23] Specifically, we use the results of the Gender-Career Implicit Association Test, which measures the extent to which test-takers associate females and males with having a career versus staying at home to take care of the family.

Table 9
Robustness to Controlling for County Characteristics

This table shows the robustness of the results in Table 8 to controlling for the interaction between minority dummies and various county characteristics:

$$\textit{Emergency loan}_{c,f,r,z} = \alpha_z + \beta \cdot \textit{Black}_f + \theta \cdot \textit{Black}_f \times \textit{Racial bias}_c + \phi \cdot \textit{Black}_f \times X_c + \gamma' X_{f,r} + \varepsilon_{c,f,r,z},$$

where c indexes counties, f indexes firms, r indexes restaurants, and z indexes ZIP codes. County-level averages of racial bias are standardized so that the interaction terms represent the effect of a one standard deviation increase in racial bias. Regressions are weighted by the number of white respondents to the Race Implicit Association Test during 2008–2019 period. Standard errors are adjusted for clustering by county. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. $N = 10,888$.

	Bank PPP		Nonbank PPP		EIDL	
	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.300***	−0.219***	0.085**	0.027	0.027	0.066***
	(0.032)	(0.025)	(0.033)	(0.043)	(0.023)	(0.025)
Hispanic	−0.037	−0.037	−0.012***	−0.012***	0.066***	0.066***
	(0.024)	(0.024)	(0.003)	(0.003)	(0.016)	(0.016)
Asian	−0.047**	−0.046**	0.061***	0.061***	0.020	0.020
	(0.020)	(0.020)	(0.016)	(0.016)	(0.033)	(0.033)
Other	−0.031	−0.031	0.032*	0.032*	0.052***	0.053***
	(0.029)	(0.029)	(0.017)	(0.017)	(0.020)	(0.020)
Female	−0.038***	−0.038***	0.016	0.016	−0.005	−0.005
	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)
Black × Bias	−0.158***	−0.389***	0.152**	0.259*	−0.091**	−0.180***
	(0.058)	(0.105)	(0.069)	(0.135)	(0.038)	(0.062)
Black× Per capita personal income	−0.037	0.034	−0.022	−0.061**	0.062***	0.092***
	(0.023)	(0.033)	(0.020)	(0.026)	(0.018)	(0.020)
Black× Unemployment rate	0.048	0.112***	−0.011	−0.042	0.157***	0.182***
	(0.042)	(0.037)	(0.032)	(0.045)	(0.034)	(0.038)
Black× White population share	0.043	0.025	0.040	0.051	−0.114***	−0.122***
	(0.038)	(0.026)	(0.033)	(0.030)	(0.037)	(0.037)
Black× Ln(Population)	0.155***	0.162***	0.072	0.054	−0.095**	−0.087**
	(0.052)	(0.046)	(0.065)	(0.060)	(0.039)	(0.035)
Ln(Seats)	0.063***	0.063***	−0.009***	−0.009***	0.004	0.004
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)
Ln(Firm age)	0.033***	0.033***	−0.004	−0.004	−0.019***	−0.019***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.007)	(0.007)
Bank UCC loan	0.085***	0.085***	−0.029***	−0.029***	0.052***	0.052***
	(0.015)	(0.015)	(0.005)	(0.005)	(0.012)	(0.012)
Nonbank UCC loan	0.033**	0.032**	0.035***	0.035***	0.098***	0.098***
	(0.016)	(0.015)	(0.013)	(0.013)	(0.008)	(0.008)
R^2	0.150	0.150	0.095	0.094	0.092	0.092
ZIP FEs	✓	✓	✓	✓	✓	✓

5.1 Distance to bank PPP lenders

In addition to substituting to nonbanks, Black-owned restaurants in counties with stronger racial bias may have to search for more distant banks that may be located in areas with less

racial bias. Table 10 examines this hypothesis. Within the sample of restaurants that receive bank PPP loans, we measure borrower-lender distance as the geodesic distance between the restaurant and the closest branch of the bank extending the PPP loan. We use June 2019 Summary of Deposits data on the location of bank branches.

Raw distance is highly skewed. While the median distance is only 1.7 miles, the mean is 129 miles. Less than 11% of all restaurants that receive a bank PPP loan borrow from a bank whose closest branch is at least 129 miles away. To prevent outliers from affecting the results, we create binary dependent variables for whether the closest branch of the firm's PPP bank lender is more than 10 (25) miles away. About 19% (14%) of all restaurants that receive bank PPP loans are located more than 10 (25) miles away from the closest branch of their PPP bank.

In columns 1–2 the dependent variable is equal to one if the closest branch of the PPP bank is at least 10 miles away. In columns 3–4 the dependent variable is equal to one if the closet branch of the PPP bank is at least 25 miles away. Columns 1 and 3 report the results for explicit bias, while columns 2 and 4 report the results for implicit bias.

We find a large positive interaction between *Black* and racial bias. A one standard-deviation increase in county-level racial bias is associated with 37–39 percentage points increase in the probability that a Black-owned restaurant receives its bank PPP loan from a distant bank. This is a large effect compared to the unconditional probability of borrowing from a distant bank. We also find a positive and statistically significant interaction between *Asian* and racial bias, and some evidence of a positive interaction between *Female* and racial bias.

The coefficient of firm age is negative and statistically significant, indicating that older firms are less likely to borrow from a distant bank. The coefficient on bank UCC loan is not statistically significant while the coefficient on nonbank UCC loan is positive and statistically significant. The fact that a firm has a nonbank UCC loan may indicate that nearby banks were previously unwilling to lend to the firm. As a result, the firm may have had to approach more distant banks for its PPP loan.

5.2 Third round of PPP

To improve access to the program by small and minority-owned businesses, the Small Business Administration instituted a number of changes to the program in the third round of PPP, which began on January 11, 2021. These include setting aside funds for the following:

Table 10
Racial Bias and Distance to Bank PPP Lenders

This table reports the results of linear probability model regressions of large distance between restaurants and their bank PPP lenders:

$$I(\textit{Borrower-lender distance} > X \textit{ miles})_{c,f,r,z} = \alpha_z + \beta \cdot Minority_f + \delta \cdot Female_f + \theta \cdot Minority_f \times \textit{Racial bias}_c + \gamma' X_{f,r} + \varepsilon_{c,f,r,z},$$

where c indexes counties, f indexes firms, r indexes restaurants, and z indexes ZIP codes. Borrower-lender distance is the geodesic distance between a restaurant and the closest branch of its bank PPP lender. The sample consists of restaurants that received bank PPP loans. The share of restaurants receiving bank PPP loans from banks located more than 10(25) miles away is 19%(14%). County-level averages of racial bias are standardized so that the interaction terms represent the effect of a one standard deviation increase in racial bias. Regressions are weighted by the number of white respondents to the Race Implicit Association Test during 2008–2019 period. Standard errors are adjusted for clustering by county. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. $N = 7,312$.

	Borrower-bank distance >			
	10 miles		25 miles	
	Explicit	Implicit	Explicit	Implicit
	(1)	(2)	(3)	(4)
Black	0.209***	0.062	0.236***	0.081*
	(0.043)	(0.046)	(0.045)	(0.046)
Hispanic	−0.036	−0.045***	−0.038**	−0.042***
	(0.029)	(0.017)	(0.019)	(0.013)
Asian	0.062**	−0.006	0.085***	0.013
	(0.029)	(0.022)	(0.029)	(0.023)
Other	0.052	0.006	0.081*	0.031
	(0.045)	(0.039)	(0.041)	(0.041)
Female	0.029***	0.014***	0.033***	0.023***
	(0.009)	(0.005)	(0.011)	(0.006)
Black × Bias	0.369***	0.371*	0.390***	0.380*
	(0.125)	(0.213)	(0.125)	(0.218)
Hispanic × Bias	0.027	0.050	0.015	0.033
	(0.043)	(0.043)	(0.032)	(0.035)
Asian × Bias	0.162***	0.195**	0.175***	0.198**
	(0.053)	(0.086)	(0.049)	(0.091)
Other × Bias	0.109	0.184**	0.123**	0.165**
	(0.079)	(0.080)	(0.055)	(0.067)
Female × Bias	0.037**	0.051***	0.026	0.030*
	(0.015)	(0.014)	(0.016)	(0.016)
Ln(Seats)	−0.009	−0.010	−0.007	−0.008
	(0.007)	(0.007)	(0.007)	(0.007)
Ln(Firm age)	−0.020***	−0.020***	−0.022***	−0.022***
	(0.005)	(0.005)	(0.006)	(0.006)
Bank UCC loan	0.026	0.026	−0.001	−0.001
	(0.017)	(0.017)	(0.013)	(0.013)
Nonbank UCC loan	0.037**	0.038**	0.041***	0.042**
	(0.016)	(0.017)	(0.015)	(0.016)
R^2	0.147	0.146	0.133	0.131
ZIP FEs	✓	✓	✓	✓

lending by Community Financial Institutions (CFIs) and by banks with less than $10 billion in assets; lending to new PPP borrowers; lending to small firms with at most 10 employees; and lending less than $250,000 to borrowers in low- or moderate-income neighborhoods. The SBA also provided a window of exclusive access to the program by CFIs with less than $1 billion in assets. We explore whether these changes mitigated racial disparities in the program.

The results in Table 11, which use data running from January 12 through June 30, 2021, suggest a fairly significant attenuation in racial disparities in the case of Black-owned restaurants, although disparities remain. Columns 1–2 report the results for bank PPP lending, columns 3–4 report the results for nonbank PPP lending, and columns 5–6 report the results for any PPP loan. Controlling for location, firm size, age, and existing UCC lending relationships, and interactions with local racial bias measures, we find that Black-, Hispanic-, and Asian-owned restaurants are 10.7% (11.8%), 5.5% (3.1%), and 0.1% (2.4%) less likely to receive bank PPP loans using explicit (implicit) measures of racial bias. Restaurants owned by women are 3.5% (3.8%) less likely to receive bank PPP loans. As before, we have normalized racial bias to be mean zero with unit standard deviation, so the coefficient of the minority restaurant-owner dummies reflects the effect for the county with average racial bias.

Comparing the first columns of Table 11 and Table 8, both of which uses the explicit bias measure, we see that Black-owned restaurants go from being 25.2% less likely to receive a bank PPP loan in the first two rounds of PPP to being 10.7% less likely to receive a bank PPP loan in the third round of PPP. The reduction is somewhat smaller using the implicit bias measure, but still statistically significant. There is also a reduction in disparities for Asian-owned restaurants, although the reduction is not statistically significant using the implicit bias measure. At the same time, when we look at nonbank PPP lending in columns 3–4 in Table 11 and compare the results with columns 3–4 in Table 8, we see a relative decline in the probability that minority-owned restaurants receive nonbank PPP loans. In particular, the coefficient on *Black* declines from 9.9% to 5.7% using the explicit bias measure, while the coefficient on *Asian* declines from 9.3% to 5.4%. Finally, in the third round of PPP we do not see a significantly lower probability that Black-owned restaurants receive PPP from banks in more racially biased counties and we do not see a correspondingly higher probability that they receive nonbank PPP funding in those counties. Both effects were observed in earlier PPP rounds.

Table 11
Round 3 of PPP

This table reports the results of linear probability model regressions of the utilization of PPP loans during the third round of the program from January 12 through April 30, 2021. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. $N = 10,888$.

	Bank PPP		Nonbank PPP		PPP	
	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.107***	−0.118***	0.057***	0.022*	−0.051	−0.096***
	(0.038)	(0.022)	(0.016)	(0.013)	(0.038)	(0.025)
Hispanic	−0.055***	−0.031*	0.006	−0.003	−0.049***	−0.034**
	(0.017)	(0.016)	(0.015)	(0.009)	(0.017)	(0.014)
Asian	−0.001	−0.024*	0.054***	0.046***	0.053**	0.022
	(0.022)	(0.014)	(0.018)	(0.011)	(0.020)	(0.015)
Other	−0.032	−0.062***	0.048*	0.043**	0.016	−0.020
	(0.020)	(0.018)	(0.028)	(0.020)	(0.033)	(0.030)
Female	−0.035**	−0.038***	0.021***	0.011***	−0.015	−0.027**
	(0.013)	(0.011)	(0.007)	(0.002)	(0.014)	(0.011)
Black × Bias	0.021	0.071	0.089***	0.090***	0.110*	0.160***
	(0.073)	(0.070)	(0.023)	(0.033)	(0.059)	(0.049)
Hispanic × Bias	−0.055	−0.060	0.023	0.021	−0.032	−0.039
	(0.044)	(0.051)	(0.019)	(0.030)	(0.045)	(0.050)
Asian × Bias	0.054	0.091**	0.021	0.006	0.074*	0.097***
	(0.042)	(0.043)	(0.020)	(0.024)	(0.039)	(0.035)
Other × Bias	0.075	0.076	0.013	0.008	0.088	0.085
	(0.048)	(0.049)	(0.044)	(0.061)	(0.077)	(0.093)
Female × Bias	0.007	0.022	0.023**	0.036***	0.030	0.057***
	(0.021)	(0.023)	(0.011)	(0.012)	(0.019)	(0.020)
Ln(Seats)	0.073***	0.073***	−0.002	−0.002	0.072***	0.072***
	(0.009)	(0.009)	(0.003)	(0.003)	(0.011)	(0.011)
Ln(Firm age)	0.008	0.008	−0.003	−0.003	0.005	0.005
	(0.006)	(0.006)	(0.002)	(0.002)	(0.008)	(0.008)
Bank UCC loan	0.051***	0.052***	−0.017**	−0.017**	0.034*	0.034*
	(0.016)	(0.017)	(0.008)	(0.008)	(0.017)	(0.017)
Nonbank UCC loan	0.066***	0.066***	0.030***	0.030***	0.096***	0.097***
	(0.020)	(0.019)	(0.011)	(0.011)	(0.018)	(0.017)
R^2	0.137	0.137	0.085	0.085	0.132	0.132
ZIP FEs	✓	✓	✓	✓	✓	✓

6 Robustness and External Validity

6.1 Robustness

The restaurant license data we have used so far allows us to control for restaurant size and age, but does not include more detailed information on the type of restaurant and customer visits. It is possible that certain types of restaurants were more vulnerable to the pandemic and thus were more likely to shut down, if only temporarily. It is also possible

that restaurants that were less popular and perhaps marginally profitable before the pandemic were also more likely to shut down. If minority-owned restaurants are the types that were more vulnerable to the pandemic or were less profitable pre-pandemic, the minority restaurant-owner coefficients could be biased upwards in magnitude.

To address these concerns we use data from SafeGraph on restaurant characteristics, average number of monthly visits, and the median dwell time at the restaurant during 2019. SafeGraph collects anonymous data on visits to different points of interest using cell phone tracking.[24] In addition to the average number of monthly visits and median dwell time, which could crudely proxy for pre-pandemic profitability when also controlling for restaurant size, we use restaurant category tags collected by SafeGraph. These tags include the types of meals served (e.g. breakfast, lunch, brunch, dinner), types of food served (e.g. pizza, burgers), cuisine (e.g., Italian, Mexican), and mode of serving (e.g., counter service, drive-through). A given restaurant can have multiple tags assigned to it. We create dummy variables for the 20 most frequently used tags. We restrict the sample to restaurants that have at least one tag in SafeGraph data. The resulting sample accounts for 68% of restaurants in the full sample. For brevity we do not report the coefficients on the restaurant type dummies.

The results in Table 12 indicate that restaurants that had more pre-pandemic visits were more likely to receive bank PPP funding (column 3). Importantly, the coefficients on the minority restaurant-owner dummies are little affected by the inclusion of the SafeGraph data as can be seen by comparing the coefficients in column 2, which reports the regression results without the SafeGraph data but for the same sample as column 3. Compared to the full sample, reported in column 1 (replicating the results in column 1 of Table 7), the magnitude of the coefficient on *Black* is somewhat smaller, while the magnitude of the coefficients of the other minority restaurant-owner dummies are larger. Not surprisingly, given these findings, restaurants with more pre-pandemic visitors are less likely to receive nonbank PPP funding and EIDL funding. The coefficients on the minority restaurant-owner dummies are also little affected as shown in columns 4–9. It seems safe to conclude from these findings that estimated racial disparities in bank PPP funding are not affected in any material way by the inclusion of detailed data on restaurant characteristics and visits.

Table 13 shows the robustness of our results to a number of alternative specifications. For brevity we report only the results for bank PPP loans. We report the results with and without controls for firm characteristics and bank relationships.

[24] SafeGraph partners with mobile apps that obtain consent from their users to collect location data. SafeGraph uses the raw geographic coordinates of a user's cell phone to determine the store, restaurant, or another point of interest that the user was visiting when their cell phone pinged.

Table 12
Controlling for Restaurant Type and Customer Visits before the Pandemic

This table shows the robustness of the results in Table 5 to controlling for restaurant type, number of visits before the pandemic, and median time spent at the restaurant. Restaurant type, number of visits, and median dwell time are from SafeGraph. Number of visits is the average number of monthly visits during 2019. Only establishments with valid restaurant category tags and median dwell time of less than three hours are included in the analysis using SafeGraph data. Restaurant type dummies are binary variables for the presence of each of the following category tags: Breakfast, Brunch, Lunch, Dinner, Late night, Counter service, Fast food, Coffee shop, Sandwich shop, Pizza, Burgers, American, Italian, Catering, Dessert, Seafood, Mexican, Bakery, Drive-through, Bar or pub. These are the twenty most frequently used tags for Florida restaurants. Regressions in columns 2, 5, and 8 are limited to observations with valid SafeGraph data. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Bank PPP			Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black	−0.198***	−0.170***	−0.174***	0.053***	0.057**	0.061***	0.033	0.066**	0.067**
	(0.026)	(0.032)	(0.032)	(0.018)	(0.023)	(0.023)	(0.027)	(0.033)	(0.033)
Hispanic	−0.043***	−0.055***	−0.073***	−0.002	0.001	0.012	0.051***	0.046**	0.050**
	(0.015)	(0.018)	(0.020)	(0.007)	(0.009)	(0.010)	(0.015)	(0.019)	(0.021)
Asian	−0.044***	−0.061***	−0.057***	0.075***	0.084***	0.085***	0.039**	0.029	0.028
	(0.017)	(0.019)	(0.020)	(0.011)	(0.013)	(0.013)	(0.017)	(0.020)	(0.021)
Other	−0.030	−0.032	−0.031	0.029**	0.023	0.025	0.057**	0.055*	0.056*
	(0.025)	(0.029)	(0.029)	(0.014)	(0.016)	(0.016)	(0.025)	(0.030)	(0.030)
Female	−0.029***	−0.031**	−0.032**	0.011*	0.013*	0.012*	−0.006	−0.009	−0.015
	(0.011)	(0.013)	(0.013)	(0.006)	(0.007)	(0.007)	(0.011)	(0.013)	(0.013)
Ln(Seats)	0.067***	0.079***	0.080***	−0.008***	−0.010***	−0.007*	0.003	0.002	0.010
	(0.005)	(0.006)	(0.007)	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)
Ln(Firm age)	0.033***	0.039***	0.035***	−0.005**	−0.005*	−0.004	−0.025***	−0.017***	−0.012**
	(0.005)	(0.006)	(0.006)	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)	(0.006)
Bank UCC loan	0.093***	0.060***	0.066***	−0.027***	−0.020***	−0.018**	0.053***	0.056***	0.077***
	(0.012)	(0.015)	(0.015)	(0.006)	(0.007)	(0.007)	(0.013)	(0.017)	(0.017)
Nonbank UCC loan	0.048***	0.044***	0.041**	0.027***	0.030***	0.031***	0.098***	0.108***	0.103***
	(0.013)	(0.016)	(0.016)	(0.008)	(0.010)	(0.010)	(0.014)	(0.018)	(0.018)
Ln(Monthly visits)			0.022***			−0.006**			−0.017***
			(0.005)			(0.003)			(0.005)
Ln(Median dwell time)			−0.007			−0.005			0.013
			(0.011)			(0.006)			(0.011)
N	10,888	7,408	7,408	10,888	7,408	7,408	10,888	7,408	7,408
R^2	0.164	0.203	0.214	0.104	0.144	0.149	0.103	0.134	0.149
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Restaurant type dummies			✓			✓			✓

Table 13
Robustness

This table shows the robustness of the results in Table 5 to alternative specifications. The sample consists of restaurants with seating that were licensed before February 15, 2020, whose license holders are Florida for-profit firms registered before February 15, 2020, and whose owner's race can be identified using Florida voter registration data. Hotel and franchise restaurants are excluded. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Single-restaurant firms		Loans by affiliates		Census tract		Census block group	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	−0.332***	−0.184***	−0.356***	−0.214***	−0.238***	−0.174***	−0.237***	−0.182***
	(0.024)	(0.027)	(0.023)	(0.026)	(0.032)	(0.032)	(0.040)	(0.040)
Hispanic	−0.109***	−0.047***	−0.120***	−0.060***	−0.060***	−0.033*	−0.055**	−0.033
	(0.013)	(0.016)	(0.013)	(0.015)	(0.018)	(0.018)	(0.022)	(0.021)
Asian	−0.088***	−0.035**	−0.108***	−0.055***	−0.080***	−0.032*	−0.078***	−0.031
	(0.016)	(0.017)	(0.016)	(0.016)	(0.020)	(0.020)	(0.024)	(0.024)
Other	−0.073***	−0.029	−0.091***	−0.045*	−0.059**	−0.034	−0.058*	−0.036
	(0.025)	(0.026)	(0.024)	(0.024)	(0.029)	(0.029)	(0.035)	(0.034)
Female	−0.064***	−0.031***	−0.080***	−0.044***	−0.049***	−0.025**	−0.055***	−0.032**
	(0.011)	(0.011)	(0.010)	(0.010)	(0.012)	(0.012)	(0.015)	(0.015)
Ln(Seats)		0.075***		0.077***		0.065***		0.060***
		(0.005)		(0.005)		(0.006)		(0.007)
Ln(Firm age)		0.032***		0.029***		0.033***		0.035***
		(0.005)		(0.005)		(0.006)		(0.007)
Bank UCC loan		0.091***		0.093***		0.095***		0.097***
		(0.013)		(0.011)		(0.014)		(0.017)
Nonbank UCC loan		0.057***		0.039***		0.046***		0.043**
		(0.014)		(0.012)		(0.015)		(0.018)
N	10,041	10,041	10,888	10,888	10,888	10,888	10,888	10,888
R^2	0.030	0.169	0.039	0.181	0.324	0.351	0.468	0.488
ZIP FEs	✓	✓	✓	✓				
Census tract FEs					✓	✓		
Census block group FEs							✓	✓

In columns 1–2, we restrict the sample to single-restaurant firms, which account for 92% of the sample.[25] We find very similar results. In columns 3–4, we redefine the dependent variable to be equal to one if either the firm itself or any of its affiliates receives a bank PPP loan. We consider two firms to be affiliated if they have the same first officer.[26] We find somewhat stronger results when incorporating information about PPP loans received by affiliates. Compared to column 2 in Table 7, the coefficient on *Black* increases in magnitude from -20.0% to -21.6%, the coefficient on *Hispanic* increases in magnitude from -4.5% to -6.2%, the coefficient on *Asian* increases in magnitude from -4.2% to -5.3%, and the coefficient on *Female* increases in magnitude from -3.0% to -4.4%.

Finally, in columns 5–8, we examine robustness to more granular location fixed effects. These regressions are meant to address the concern that even within a ZIP code, minority-owned restaurants may be located farther away from bank branches, in particular from banks that are active PPP lenders. We obtain 2010 Census tract and block information from the Census geocoder[27] and Texas A&M GeoServices.[28] Because Census geocoder has weak coverage of non-residential addresses, we first run restaurant addresses through Census geocoder, and then run the unmatched addresses through Texas A&M GeoServices. Columns 5–6 use Census tract fixed effects, while columns 7–8 use Census block group fixed effects. There are 838 ZIP codes, 2,861 Census tracts, and 4,465 Census block group in the data. We find similar results when comparing minority- and white-owned restaurants within these more narrowly defined geographic areas.

6.2 External validity

One may wonder whether there is something special about restaurants and whether the results apply to other industries. After all, restaurants were hit especially hard by the pandemic due to restrictions on dining inside. To address this question we look at all PPP and EIDL borrowers in Florida. We can no longer study the population of potential borrowers and ask which ones access PPP and EIDL funding and which ones do not.

[25] This classification is based on the restaurant's license holder (immediate owner) and does not account for restaurants owned by affiliated firms.

[26] Specifically we match on the first officer's first and last names, city, ZIP code, and street address.

[27] https://geocoding.geo.census.gov/geocoder/

[28] https://geoservices.tamu.edu

We start by matching PPP and EIDL borrowers to Florida corporate records. Restricting the sample to Florida-based for-profit firms, we combine PPP and EIDL borrowers into one sample. We then estimate regressions of the probability that firms in this pooled sample receive bank PPP loans.

There is likely to be significant variation in the share of minority-owned businesses within an industry and in the utilization of emergency loans across industries. While PPP data include NAICS industry classification, this information is not available in the EIDL data. To control for industry, we match PPP and EIDL borrowers to data from Dun & Bradstreet using information about borrower's name and location.

Borrower names in our version of the Dun & Bradstreet database are abbreviated in various ways to be at most 30 characters. As a result of differences in spelling, we are able to match about two-thirds of PPP and EIDL borrowers to the Dun & Bradstreet database.

Dun & Bradstreet also provides data on each firm's sales and number of employees. However, in the vast majority of cases, sales numbers are modelled by Dun & Bradstreet rather than being actual numbers reported by the firm. Measurement error in sales is likely to significantly bias the coefficients on sales towards zero. Thus, regressions that control for sales should be interpreted with caution.

Table 14 reports the results. Column 1 reports regressions in which the dependent variable is whether the firm receives a bank PPP loan. Minority business-owner dummies are included as explanatory variables without location, industry, or firm characteristics. Relative to white-owned businesses, Black-, Hispanic-, and Asian-owned businesses are 38.9%, 24.1%, and 5.5% less likely to receive bank PPP loans. Female-owned businesses are 2.7% less likely to receive bank PPP loans.

Column 2 adds ZIP and industry (SIC) fixed effects. These reduce the magnitude of the minority business-owner dummies by 20–30%. The largest percentage reduction is for the coefficient on *Hispanic*, which is reduced in magnitude from -24.1% to -17.2%. Column 3 uses ZIP cross industry fixed effects, thereby comparing firms in the same industry and the same ZIP code. The coefficients in column 3 are broadly similar to the ones in column 2.

Column 4 adds firms characteristics: age, sales, and number of employees. Consistent with the results for restaurants, older and larger firms are more likely to receive bank PPP loans. The coefficients on *Black*, *Hispanic*, and *Asian* in column 4 are -23.1%, -12.0%, and -3.4%. The coefficient on *Female* is reduced in magnitude to -0.8% and is statistically significant at 10%.

Table 14
External Validity: Utilization of Bank PPP Loans

This table reports the results of linear probability model regressions of receiving bank PPP loans. The sample consists of all PPP and EIDL borrowers that can be matched to Florida corporate records, voter registration, and Dun & Bradstreet. Industry classification, sales, and number of employees are from Dun & Bradstreet. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)
Black	−0.389***	−0.313***	−0.294***	−0.231***	−0.228***
	(0.005)	(0.006)	(0.009)	(0.009)	(0.009)
Hispanic	−0.241***	−0.172***	−0.161***	−0.120***	−0.120***
	(0.003)	(0.004)	(0.007)	(0.007)	(0.007)
Asian	−0.055***	−0.056***	−0.063***	−0.034***	−0.034***
	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)
Other	−0.127***	−0.102***	−0.113***	−0.083***	−0.081***
	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)
Female	−0.027***	−0.021***	−0.022***	−0.008*	−0.006
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
Ln(Firm age)				0.059***	0.058***
				(0.003)	(0.003)
Ln(Sales)				0.050***	0.043***
				(0.003)	(0.003)
Ln(Employees)				0.013**	0.008
				(0.005)	(0.005)
Bank UCC loan					0.106***
					(0.005)
Nonbank UCC loan					0.028***
					(0.007)
N	131,465	131,069	131,465	131,465	131,465
Adjusted R^2	0.073	0.138	0.133	0.178	0.184
ZIP FEs		✓			
SIC FEs		✓			
SIC-ZIP FEs			✓	✓	✓

Finally, column 5 adds dummies for having bank and nonbank UCC loans. We once again find that both bank and nonbank UCC loans are associated with greater probability of receiving bank PPP loans, but the effect of bank UCC loans is much larger than the effect of nonbank UCC loans. Furthermore, once again, UCC loan dummies do not have much effect on the coefficients of the minority business-owner variables.

7 Conclusion

We have explored racial disparities in the Paycheck Protection Program using detailed data on Florida restaurants and their owners. Disparities exist not just because minority-owned businesses tend to be located in areas with fewer bank branches, as has been suggested by prior research, but even within the same ZIP code, Census tract, and Census block,

minority-owned firms are less likely to receive PPP loans from banks. Nonbank lenders, largely fintechs, lend more to minority-owned businesses but they are a relatively small share of PPP lending so that in aggregate there are still racial disparities in the program. Minority-owned businesses are also more likely to access EIDL loans, another type of emergency loan, in which firms apply directly to the SBA.

The fact that minority-owned businesses received more funding from nonbanks as well as EIDL loans directly from the SBA suggests that lower loan demand does not explain the lower take-up rate of PPP loans by minority-owned businesses. Instead, our findings indicate that there were aspects of PPP lending by banks that disadvantaged minority-owned businesses. Our evidence suggests that racial bias played a direct or indirect role in the lower utilization of bank PPP loans by minority-owned businesses. Specifically, we find that Black-owned restaurants were much less likely to receive PPP loans from banks in counties in which there is more implicit or explicit racial bias.

While racial bias is related to racial disparities in PPP, more work needs to be done to understand why. One possibility is that racially-biased bank loan officers responsible for originating PPP loans treated Black applicants less well than white applicants. This explanation is consistent with the audit studies conducted by the National Community Reinvestment Coalition (National Community Reinvestment Coalition, 2020b,a). However, it is also possible that racial bias and history of discrimination discouraged Black-owned firms from applying for bank PPP loans.

Another possibility is that Black business owners are less likely to have bank relationships in more racially biased areas because they had directly experienced poor treatment when seeking banking services or because a history of mistreatment discouraged them from seeking such services in the first place. If banks favored their most valued existing customers in allocating scarce resources to the large volume of PPP loan applications, this history of bias would also manifest in racial disparities in PPP lending.

We do not find that a history of secured borrowing from a bank mitigates racial disparities in PPP. Indeed, while such borrowing does help white-owned restaurants gain access to PPP loans, there is no such benefit for Black-owned restaurants. This suggests that, in addition to having greater problems accessing bank loans, Black-owned businesses likely have weaker relationships to their bank lenders even when they are able to access these loans.

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Appendix

Linking approved PPP loans to Florida corporate records

1. We start with the sample of borrower who according to PPP data are located in Florida. Some of these will turn out to be firms registered in other states and will be dropped after linking to Florida corporate records.

2. Because our focus in on for profit incorporated businesses, we drop non-profits, cooperatives, employee stock ownership plans (ESOPs), joint ventures, partnerships, professional associations, and a few other rare business types. Business types remaining in the sample are

   - Corporation
   - Independent Contractors
   - Limited Liability Company (LLC)
   - Limited Liability Partnership
   - Self-Employed Individuals
   - Sole Proprietorship
   - Subchapter S Corporation

   We keep independent contractors, self-employed individuals, and sole proprietorships at this point because while most of these borrowers report individual names, some are in fact set up as firms. We drop a small number of borrowers whose names are missing or identify borrowers simply as an Uber or Lyft driver or an independent contractor without providing any other information.

3. Match exactly on firm name after removing punctuation and standardizing legal form (for example replacing "Corporation" with "Corp").

4. Match exactly on firm name after removing white space.

5. Match after removing legal form.

6. Set aside borrowers that have not been matched up to this point and that can be matched to Florida voter registration or white pages data. We parse borrower name into first and last names, and try to match these to voter registration data. If there is at least one match in voter registration data, we tag borrower as an individual.

7. Fuzzy match based on borrower name, ZIP, and street address. We require an exact match on ZIP and first five letters of firm name.

Linking restaurants to corporate records

1. Match restaurant license holder name to firm name in corporate records after removing punctuation and standardizing legal form. To break ties between multiple potential matches, we use the following screens.

   (a) If there is a match that is currently active according to corporate records, drop inactive matches.

   (b) If there is a match that has the same ZIP code, drop firms that do not match on ZIP code. We compare the principal address in corporate records with the restaurant location and the mailing address in corporate records with the license holder mailing address.

   (c) If there is a match with the same city name, drop firms that do not match on city name.

   (d) Keep only those licenses that match to a single corporate record.

2. Remove white space from license holder and firm names and repeat step 1 on unmatched restaurants.

3. Remove legal form from license holder and firm names and repeat step 1 on unmatched restaurants.

4. Try matching restaurant name to firm name in corporate records after removing punctuation and legal form. Apply the same procedure for breaking ties as in step 1.

5. Fuzzy match between license holder name and firm name.

   (a) Match on ZIP code and first three letters of license holder and firm names.

   (b) Calculate similarity score between license holder and firm names. We use bigram string matching method and calculate the Jaccard score. Specifically we split each name into bigrams, i.e., all possible sequences of two letters. The similarity score between two strings is then $\frac{m}{\sqrt{s_1 \times s_2}}$, where m is the number of bigrams the two strings have in common, and s_1 and s_2 are the numbers of birgram in the two strings.

(c) Consider the firm with the highest similarity score to be a match if the similarity score is greater than 0.80 and the difference compared to the next highest similarity score is at least 0.10.

6. Repeat step 5 but matching on city instead of ZIP code.

7. Fuzzy match between license holder name and first officer name in corporate records. Because a first officer can be affiliated with multiple firms in corporate records we keep only those cases where the first officer is affiliated with only one firm. We follow the same general approach as in step 5 except that we

   (a) Match on the first five letters of license holder and first officer names.

   (b) Require similarity score of the best match to be at least 0.95 and at least 0.05 larger than the similarity score of the next best match.

8. Match restaurant name to Florida fictitious records data that report owners of fictitious names including restaurants. Many owners either do not register their fictitious names or fail to update their registration. We implement a fuzzy match, first matching on ZIP code and first five letters of the restaurant/fictitious name. We require similarity score of the best match to be at least 0.95 and at least 0.05 larger than the similarity score of the next best match. Fictitious names owned by individuals are excluded.

Table A1
Linking Restaurants to Corporate Records

This table summarizes the link between Florida restaurants and corporate records.

Step	#	%
Eligible restaurants	25,754	100.0%
1. License holder name - firm name	19,353	75.1%
2. without white space	507	2.0%
3. without legal form	996	3.9%
4. Restaurant name - firm name	1,457	5.7%
5/6. Fuzzy match between license holder and firm name	942	3.7%
7. License holder name - first officer	0	0.0%
8. Restaurant name - fictitious names	281	1.1%
Unmatched	2,218	8.6%

Linking restaurant owners to voter registration

We combine two snapshots of Florida voter registration data: January 31, 2017 and January 31, 2021.[29] The most recent snapshot accounts for 89% of all voter records. The older snapshot includes voters who may have been deregistered for various

While we have street address for both restaurant owners and voters, we do not match on street address for two reasons. First, officer's address in corporate records can be a business instead of residential address. Second, corporate records report the most recent address, while voter registration data report the address at the time of registration. If a voter moved within a county and did not update voter registration, the address in voter registration data will be an old address that will not match the address in corporate records, which is updated at least annually. For these reasons we use street address only to break ties between multiple potential matches.

1. Drop restaurants whose first officer is not a person or whose first officer has an out-of-state mailing address.
2. Parse officer name into components: last, first, middle, suffixes and credentials.
3. Match based on county, first and last names.[30]
   (a) If both owner and voter have middle initials, check that the initials agree. If they do not, drop potential matches. Note that we do not rule out matches where only one of the names includes middle initial or name.
   (b) Similarly, if both owner and voter names include a suffix like Jr or II, check for agreement and drop potential that disagree.
   (c) If there is a unique match, keep it.
4. If there are multiple matches, try to break ties using city and street address.
   (a) Drop potential matches whose city does not match.
   (b) Calculate similarity score between street addresses. Keep the best match if its similarity score is at least 0.80 and is at least 0.05 larger than the next highest similarity score.

[29] https://dos.myflorida.com/elections/data-statistics/voter-registration-statistics/voter-extract-disk-request/

[30] We map ZIP codes into counties using HUD USPS ZIP Code Crosswalk Files. In rare cases where a ZIP belongs to multiple counties, we use the counties that accounts for the largest share of the ZIP code.

5. If after the previous step there are still multiple potential matches, but they all report the same race, use that race.

Table A2
Nonbank Lenders

This table lists nonbank lenders extending PPP loans to restaurants in our data.

Lender	***N***	**%**
CROSS RIVER BANK	534	22.0
KABBAGE	415	17.1
WEBBANK	337	13.9
CELTIC BANK CORP	313	12.9
ITRIA VENTURES LLC	201	8.3
READYCAP LENDING LLC	193	8.0
SQUARE CAPITAL LLC	60	2.5
FOUNTAINHEAD SBF LLC	51	2.1
NEWTEK SMALL BUSINESS FINANCE	41	1.7
INTUIT FINANCING	37	1.5
HARVEST SMALL BUSINESS FINANCE LLC	34	1.4
FC MARKETPLACE LLC	27	1.1
CENTERSTONE SBA LENDING	19	0.8
BSD CAPITAL LLC	19	0.8
BENWORTH CAPITAL	16	0.7
MBE CAPITAL PARTNERS	16	0.7
FUNDBOX	15	0.6
DREAMSPRING	12	0.5
LIBERTY SBF HOLDINGS LLC	10	0.4
AMERICAN LENDING CENTER	8	0.3
A10CAPITAL LLC	7	0.3
ASCENDUS	7	0.3
SUNSHINE STATE ECONOMIC DEVELOPMENT CORP	7	0.3
AMUR EQUIPMENT FINANCE	7	0.3
CRF SMALL BUSINESS LOAN COMPANY LLC	6	0.2
BLACK BUSINESS INVESTMENT FUND	6	0.2
TIMEPAYMENT CORP	5	0.2
CAPITAL PLUS FINANCIAL LLC	4	0.2
FIRST EQUITY MORTGAGE BANKERS	3	0.1
OPPORTUNITY FUND COMMUNITY DEVELOPMENT	2	0.1
CDC SMALL BUSINESS FINANCE CORP	2	0.1
HOPE ENTERPRISE CORP	2	0.1
FUND-EX SOLUTIONS GROUP LLC	2	0.1
INDEPENDENT DEVELOPMENT SERVICES CORP	2	0.1
IMMITO LLC	1	0.0
FARM CREDIT OF CENTRAL FLORIDA ACA	1	0.0
LIFTFUND	1	0.0
WORLD TRADE FINANCE	1	0.0

Table A3
UCC Lending Relationships

This table reports the full output of the regressions in Table 7.

	Bank PPP			Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black	−0.199***	−0.198***	−0.176***	0.055***	0.053***	0.059***	0.036	0.033	0.025
	(0.026)	(0.026)	(0.029)	(0.018)	(0.018)	(0.020)	(0.027)	(0.027)	(0.029)
Hispanic	−0.048***	−0.043***	−0.052***	−0.000	−0.002	−0.004	0.048***	0.051***	0.047***
	(0.015)	(0.015)	(0.017)	(0.007)	(0.007)	(0.008)	(0.015)	(0.015)	(0.017)
Asian	−0.053***	−0.044***	−0.049***	0.076***	0.075***	0.077***	0.031*	0.039**	0.025
	(0.017)	(0.017)	(0.018)	(0.011)	(0.011)	(0.012)	(0.017)	(0.017)	(0.018)
Other	−0.034	−0.030	−0.037	0.029**	0.029**	0.035**	0.054**	0.057**	0.049*
	(0.025)	(0.025)	(0.028)	(0.014)	(0.014)	(0.017)	(0.025)	(0.025)	(0.029)
Female	−0.034***	−0.029***	−0.032***	0.012**	0.011*	0.007	−0.009	−0.006	−0.004
	(0.011)	(0.011)	(0.012)	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)	(0.012)
Ln(Seats)	0.074***	0.067***	0.079***	−0.008***	−0.008***	−0.006**	0.010**	0.003	0.007
	(0.005)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)
Ln(Firm age)	0.039***	0.033***	0.040***	−0.006**	−0.005**	−0.004	−0.021***	−0.025***	−0.019***
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.005)	(0.005)	(0.005)
Bank UCC loan		0.093***	0.119***		−0.027***	−0.035***		0.053***	0.038**
		(0.012)	(0.016)		(0.006)	(0.007)		(0.013)	(0.018)
Nonbank UCC loan		0.048***	0.053***		0.027***	0.038***		0.098***	0.133***
		(0.013)	(0.018)		(0.008)	(0.011)		(0.014)	(0.020)
Black× Bank UCC loan			−0.224**			0.090			0.220**
			(0.091)			(0.065)			(0.103)
Hispanic× Bank UCC loan			0.066*			0.024			0.076*
			(0.034)			(0.017)			(0.041)
Asian× Bank UCC loan			−0.011			0.063			0.184***
			(0.050)			(0.040)			(0.056)
Other× Bank UCC loan			0.052			−0.057***			0.033

(Continued)

Table A3—*continued*

	Bank PPP			Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			(0.063)			(0.021)			(0.070)
Female× Bank UCC loan			0.025			0.010			0.036
			(0.028)			(0.015)			(0.033)
Ln(Seats)× Bank UCC loan			−0.068***			0.004			−0.018
			(0.012)			(0.005)			(0.014)
Ln(Firm age)× Bank UCC loan			−0.034***			−0.004			−0.036**
			(0.013)			(0.006)			(0.015)
Black× Nonbank UCC loan			−0.008			−0.098**			−0.073
			(0.074)			(0.042)			(0.078)
Hispanic× Nonbank UCC loan			0.022			−0.009			−0.061
			(0.036)			(0.021)			(0.039)
Asian× Nonbank UCC loan			0.067			−0.086**			−0.046
			(0.051)			(0.035)			(0.057)
Other× Nonbank UCC loan			−0.014			0.012			−0.006
			(0.072)			(0.051)			(0.077)
Female× Nonbank UCC loan			−0.005			0.023			−0.043
			(0.031)			(0.020)			(0.034)
Ln(Seats)× Nonbank UCC loan			−0.015			−0.015*			−0.011
			(0.014)			(0.008)			(0.015)
Ln(Firm age)× Nonbank UCC loan			−0.039**			−0.009			−0.026
			(0.016)			(0.009)			(0.018)
	(0.006)	(0.007)	(0.008)	(0.003)	(0.004)	(0.004)	(0.007)	(0.007)	(0.008)
R^2	0.157	0.164	0.169	0.101	0.104	0.106	0.096	0.103	0.106
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓