Racial Disparities in the Paycheck Protection Program*

Sergey Chernenko†
Purdue University

David Scharfstein‡
Harvard Business School

First draft: August 18, 2021
This draft: November 3, 2021

Abstract

Using a large sample of Florida restaurants, we document significant racial disparities in the utilization of the Paycheck Protection Program (PPP) and investigate the causes of these disparities. Black-owned restaurants are 25% less likely to receive PPP loans. Restaurant location explains 5 percentage points of this differential. Restaurant characteristics gathered from license and Yelp data and prior borrowing relationships identified through lien filings can explain an additional 10 percentage points of the gap in PPP utilization. The remaining 10% disparity is driven by a 16% disparity in bank PPP lending, which is partially offset by greater nonbank PPP lending, largely from fintechs. This disparity in bank PPP loans is unlikely to be attributable to lower demand for emergency loans given the substitution to nonbank sources of PPP funding by Black-owned restaurants and their greater use of the Economic Injury Disaster Loan (EIDL) program, administered directly by the Small Business Administration. We show that Black-owned restaurants are significantly less likely to receive bank PPP loans in counties in which white people exhibit greater racial bias towards Black people. In these more racially biased counties, Black-owned restaurants substitute more to nonbank PPP loans and EIDL loans. This substitution, however, is not strong enough to eliminate racial disparities in the take-up of PPP loans.

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

*We thank Ed Glaeser, Nathan Kaplan, Olivia Kim, Ben McCartney, David Robinson, Claire Shi, Chris Stanton, Adi Sunderam and seminar participants at Carnegie Mellon University for helpful comments and suggestions, SafeGraph and Yelp for data on restaurants, and Viet-Dung Doan, Ryan Gilland, and Dean Xu for research assistance. For financial support Sergey Chernenko thanks the Blake Family Fund for Ethics, Leadership and Governance, and David Scharfstein thanks the Harvard Business School Division of Research. Disclosure: David Scharfstein is a member of the board of directors of M&T Bank Corporation, which made loans through the Paycheck Protection Program.

†Purdue University, 403 W. State Street, West Lafayette, IN 47907; email: schernen@purdue.edu
‡Harvard Business School, Soldiers Field, Boston, MA 02163; email: dscharfstein@hbs.edu

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 about $800 billion in low-interest rate loans made by financial institutions to businesses with up to 500 employees, promising to forgive these loans if borrowers maintained employment and certain other fixed expenses. A number of concerns have been raised about the design of this program, including whether it targeted businesses most needing support, whether it was subject to considerable amounts of fraud, and whether it provided equal access to minority-owned businesses.

In this paper, we provide the first systematic micro-level analysis of PPP utilization by minority-owned businesses. We document significant disparities in PPP utilization and explore the role of location, firm characteristics, borrowing relationships and racial bias in explaining these disparities. We do so by studying Florida restaurants, exploiting state administrative data on restaurant licenses, corporate records, voter registration, and lien filings, as well as detailed information on restaurants from Yelp. Restaurant license data give us the population of restaurants in Florida, almost all of which should have been eligible to receive PPP loans. From corporate records we are able to determine the identity of the restaurant owner. Voter registration data tell us the restaurant owner's self-identified race and Hispanic identity, information that is sparsely reported in PPP data and more accurate than name-based algorithms used to predict race.[1] Data on the firms' existing secured loans also enable us to examine the effect of prior lending relationships on access to PPP loans. Detailed data on restaurant characteristics from state licenses and Yelp allow us to control for differences among restaurants that could affect the supply and demand for PPP loans.

Black-owned restaurants are 25.1% less likely that white-owned restaurants to receive PPP loans. The difference is 9.1% for Hispanic-owned restaurants, and 2.2% for Asian-owned restaurants. Female-owned restaurants are 4.2% less likely to receive PPP loans. All of these disparities are statistically significant except for Asian-owned restaurants.

These disparities in overall PPP utilization are driven by disparities in bank lending. Black-owned restaurants are 33.6% less likely than white-owned restaurants to receive PPP loans from banks, while Hispanic-owned restaurants and Asian-owned restaurants are about 10% less likely. The difference for female-owned restaurants is 5.4%. Nonbank PPP lenders—largely fintechs—tend to offset these disparities in bank lending by providing loans at greater rates to Black-, Asian- and female-owned restaurants, but not Hispanic-owned restaurants. Except for Asian-owned restau-

[1] 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.

rants, the offset is only partial; Black-, Hispanic- and female-owned restaurants are still less likely than white-owned restaurants to get PPP funding, even if they are more likely to access PPP funds from nonbank lenders.

What explains these disparities in PPP lending, particularly the much lower rate of PPP utilization by Black-owned restaurants? We consider four potential explanations: (1) location; (2) firm characteristics; (3) pre-existing borrowing relationships; and (4) racial bias. All four independently help to explain disparities in PPP lending.

The first explanation, location, accounts for about 20–30% of the disparity in PPP lending to minority-owned businesses. Once ZIP code fixed effects are included in regression analyses, estimated disparities in PPP loans falls from 25.0% to 19.8% for Black-owned business and from 9.1% to 6.3% for Hispanic-owned businesses. About three-quarters of the effect of ZIP code fixed effects is due to three ZIP code characteristics: bank branches per capita, median household income and COVID cases per capita. Restaurants in ZIP codes with fewer bank branches per capita, lower household income, and more COVID cases per capita are less likely to get PPP loans.

We examine the second explanation, firm characteristics, by controlling for restaurant size, age, and a variety of other characteristics derived from Yelp data, including credit card acceptance, number of reviews and photos. These characteristics reduce disparities by another 10 percentage points for Black-owned restaurants (or 40% of the unconditional dispartity), but Black-owned restaurants are still 9.8% less likely to receive PPP loans. These disparities are little changed by adding more controls, including restaurant visits based on geolocation data from SafeGraph and employment estimates from Dun & Bradstreet. Disparities in PPP lending for Hispanic-owned businesses are cut by a similar percentage with the inclusion of these firm characteristic resulting in a fairly modest disparity in PPP loans of 3.2%.

While differences in observed firm characteristics do not completely explain disparities in bank lending, it is possible that there are unobserved characteristics that could explain these disparities. For example, it is possible that Black-owned restaurants were hit harder by the pandemic or were more vulnerable to the pandemic. In this case they might be more likely to shut down and thus not apply for bank PPP loans. However, we do not find that this is the case; controlling for observable characteristics, minority-owned restaurants are not more likely to shut down, and our findings on a restricted sample of surviving restaurants are similar to our findings on the full sample. Moreover, lower unobserved demand for PPP loans does not explain the greater use of nonbank PPP loans by minority-owned restaurants. Nor would it explain our finding that minority-owned businesses are more likely to borrow through the Economic Injury Disaster Loans (EIDL) program, an SBA disaster loan program that was expanded during the pandemic by the CARES Act and ultimately made $229 billion of loans. In this program, firms apply directly to the SBA through its website rather than through banks or other financial intermediaries. 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: 21.7% more likely for Black-owned restaurants and 5.5% for Hispanic-owned restaurants.

A third explanation for disparities in PPP lending is that minority-owned firms may have had weaker relationships with banks going into the pandemic. This 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 entirety of a banking relationship, which could include different types of loans, checking accounts, credit cards, and merchant services, we use data on Uniform Commercial Code (UCC) filings with Florida to determine whether a firm had secured loans outstanding. These loans likely capture the main variation across restaurants in their use of banking services as almost all of the restaurants in our sample accept credit cards and thus also have business checking accounts and use merchant services. We find that while minority-owned restaurants are much less likely to have bank loans outstanding, controlling for their borrowing does little to reduce the measured disparities in bank PPP borrowing. Although white-owned restaurants with loans outstanding are much more likely to get a bank PPP loan, this is not the case for Black-owned restaurants. Thus, disparities are even greater when we compare Black- and white-owned restaurants that have outstanding bank loans. 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.

The final explanation is that disparities in bank PPP lending are affected by racial bias, particularly for Black-owned businesses where disparities in bank lending are large. It is possible that racial bias exists in the way that banks process PPP loan 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 inquiries 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.[2] 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.

The portion of racial disparities not explained by our extensive controls for location, firm characteristics, and borrowing relationships is arguably attributable to racial bias. Nevertheless, it is possible that despite the inclusion of the controls there may still be unobserved factors that could explain the disparities. These unobserved factors, however, would also have to explain why Black-owned restaurants are less likely to get PPP loans but are more likely to get EIDL loans

[2] 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).

than otherwise comparable white-owned restaurants located in the same ZIP code. To alleviate concerns about unobserved factors and to provide more direct evidence of 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 towards Black people are significantly less likely to receive PPP funding from banks. The effect is large: a one standard deviation increase in explicit bias is associated with a 15.3 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 racial bias is 22.8% less likely to get a PPP loan, this implies that Black-owned restaurants in the more racially biased counties are 38.1% less likely to get a bank PPP loan than white-owned restaurants. The results using the implicit bias measure are similar. Moreover, in more racially biased counties, Black-owned businesses are much more prone to substitute to nonbank PPP lenders and EIDL loans. Both sources of emergency loans typically involve online applications, with less personal interaction than the typical bank application process. This may help to explain why Black business owners substitute to these funding sources.

We also examine whether Biden administration efforts to reduce racial disparities in the third round of PPP— 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.

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. This effectively controls for firm demand for emergency funding, and our results are similar to those for restaurants. Controlling for ZIP code cross industry fixed effects, firm age, sales, employees, and secured lending relationships, minority-owned restaurants are significantly less likely to receive bank PPP loans, and Black- and Hispanic-owned businesses are also significantly less likely to receive PPP loans overall. Moreover, Black-owned businesses are less likely to receive a bank PPP loan in more racially biased counties.

Finally, our decomposition of racial disparities into four factors—location, firm characteristics, bank relationships, and racial bias—has implications for how we evaluate the design of PPP. In particular, we show that older, larger, more heavily visited and reviewed restaurants with bank relationships were more likely to receive PPP funding. However, Black-owned restaurants tend to

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

be younger, smaller, less heavily visited and reviewed, and less likely to have bank relationships. Thus, even if there was no racial bias in the implementation of PPP, the program was used less frequently by Black-owned businesses because the features of the program made it less attractive to the types of businesses they own or because lenders found it less desirable to lend to these types of businesses.

Our paper is part of a growing literature studying the functioning and impact of PPP[4], including a number of recent studies on racial disparities in PPP. Wang and Zhang (2020) 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 location matters in accessing PPP funding, our firm-level approach allows us to look beyond location, and examine the role of firm characteristics, borrowing relationships, and racial bias. We show that ZIP code fixed effects account for only one fifth of racial disparities in PPP utilization and that firm characteristics, borrowing relationships, and racial bias are much more important in explaining racial disparities.

In a contemporaneous paper, Howell et al. (2021) show that Black-owned businesses that receive PPP funding are less likely to get funded by small banks than they are to get funded by either fintechs or the four largest banks in the full population of PPP borrowers. Both their paper and ours find that there is greater substitution of Black-owned businesses to fintechs in more racially biased locations and that controlling for prior banking relationships (measured differently) does not reduce measured disparities in bank PPP funding. Both papers also show that online loan application processes are associated with less racial disparities in PPP utilization. However, there are a number of distinctive features of our paper. First, and perhaps most importantly, because we focus on restaurants we are able to identify a set of firms that arguably all qualified for PPP. We are thus able to examine the effect of racial bias on the likelihood that a restaurant receives PPP funding, whereas Howell et al. (2021) can only examine how racial bias affects the type of lender. Our methodology allows us to conclude that even though Black-owned businesses rely more on nonbank lenders, the greater availability of this type of funding is not enough to compensate for the lower availability of bank PPP funding, thus allowing us to conclude that racial bias has real effects on PPP access. Second, by linking business owners to voter registration data we have a more accurate measure of race and ethnicity than the machine learning algorithm used in Howell et al. (2021). As argued below, such measurement error can inflate or deflate the estimated effects.

In addition to contributing to the growing literature on the Paycheck Protection Program, our

[4] See, for example, Autor et al. (2020), Bartik et al. (2020), Granja et al. (2020), Li and Strahan (2021), Hubbard and Strain (2021) and Griffin, Kruger, and Mahajan (2021)

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); Fairlie, Robb, and Robinson (2020), use survey data to show that minority-owned businesses are more likely than white-owned businesses to be turned down for bank loans and are more likely not to apply for loans for fear of being turned down. Fairlie, Robb, and Robinson (2020) show that these effects are stronger in locations with greater indications of racial bias, consistent with our findings. These studies suggest that our findings could at least in part be driven by a historical legacy of discrimination that discourages Black-owned businesses from applying for PPP loans from banks.

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 additional controls and more refined samples of restaurants, and it explores the external validity of our findings by examining 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, not through an intermediary.

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, 5) Florida voter registration, and 6) restaurant characteristics from Yelp.

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

[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

released loan-level data on the EIDL loans made after this date. In 2020 the SBA made 3.6 million loans for a total of $194 billion, while in 2021, the SBA made about 3.8 million EIDL loans for a total of $284 billion.[6] Most of our analyses, however, 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-profit organizations, we match borrowers by name to Florida corporate records. 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.

2.2 Potential borrowers

Much of the existing research on the Paycheck Protection Program is constrained by the limited data on small private firms, which comprise most of the eligible borrowers. We overcome this limitation by studying the utilization of PPP and EIDL loans by Florida restaurants.[7] 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.[8]

To have a relatively homogeneous sample, we focus on restaurants that offer seating and we exclude food trucks, takeout-only restaurants without seating, and caterers. We exclude 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 can be 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.[9] 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.[10] We classify

[6] We are not examining the much smaller EIDL Advance program, which provided up to $15,000 in grants for some EIDL applicants living in SBA-designated low-income areas.

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

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

[9] In the robustness analyses in Table 9, 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.

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

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 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 91% 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 owned by non-profits, out-of-state firms, [11] and publicly-traded firms. We also exclude restaurants matched to firms registered for the first time after February 15, 2020.

Table 1
Florida Restaurants Sample

This table summarizes the sample selection criteria and the number of restaurants at each step in the algorithm. Details of the matching algorithm are described in the Appendix.

Step	N **affected**	N **remaining**
0. Seating licenses approved before Feb 16, 2020		41,266
1. Drop out-of-state license holders	5,685	35,581
3. Drop hotel restaurants	3,218	32,363
4. Drop franchise restaurants	5,641	26,722
5. Drop restaurants operated by municipalities and JVs	96	26,626
6. Match to Florida corporate records	2,390	24,236
7. Drop firms incorporated after February 15, 2020	810	23,426
8. Drop non-profits, out-of-state, and publicly-traded firms	1,664	21,762
9. Match owner to voter registration	10,669	11,093
10. Match to Yelp	1,111	9,982

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.

Howell et al. (2021) use a machine learning algorithm to predict racial and Hispanic identity in the PPP sample based on the officer's name and the location of the business. Regression results that

[11] 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.

use predicted racial or Hispanic identity must be interpreted with caution because measurement error will cause the coefficients on the predicted identity to understate the true effect of racial or Hispanic identity, with the magnitude of bias depending on the relative accuracy with which the algorithm can classify different groups.

In addition to bias in the estimates of the direct effect of racial and Hispanic identity, measurement error is likely to be correlated with firm and location characteristics and may therefore affect the coefficients of any interaction terms. Fryer and Levitt (2008) show that adoption of distinctly Black names varies over time and is strongly correlated with socioeconomic status. This means that interactions of racial bias and firm characteristics with predicted race may capture differential measurement error rather than the effect of racial bias or firm characteristics per se. Racial bias, for example, may be correlated with distinctly Black names and thus with smaller measurement error. In regressions where the true effect of being Black is negative, the interaction of predicted Black identity with racial bias will be negative, but this does not necessarily mean that the effect of interest is stronger in more racially biased areas. Similarly, 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.[12] 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.

One further advantage of using voter registration data is that by conditioning on the owner

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

being a registered voter, we exclude restaurants that may have been ineligible for PPP funding.[13] 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 Restaurant Characteristics

Because restaurant license and corporate records data have limited information on restaurant characteristics, we supplement these administrative records data with restaurant characteristics from Yelp, a platform for crowd-sourced information and reviews about restaurants and other businesses. Using name, location, and phone information, we are able to match 90% of restaurants to Yelp. Many of the unmatched restaurant licenses are operated by golf clubs and other establishments.

Our version of Yelp data includes information on restaurant features such as whether the restaurant accepts credit cards, offers delivery, or has outside seating and user activity including the number of reviews and photos posted each week, the average rating, and the number of page visits. For each feature we know the range of dates that the feature was in place. We use features that were active before the pandemic. The cumulative number of reviews since inception and average ratings are as of February 2020. For restaurants without reviews we set the average rating to 0 and include a dummy for no reviews in our regression analyses. We also include the average number of page views and photos posted each month over the March 2019–February 2020 period.

Table 1 shows how we get from restaurants we can match to corporate records to our voter registration match and then to Yelp.

2.5 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 most of the PPP loans they hold. The list of nonbank lenders is reported in the Appendix Table A2. Most nonbank lending is done by fintechs, although not all nonbanks use more advanced financial technology to process loan applications.

[13] 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.

2.6 Bank relationships

We measure borrowing relationships 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[14], 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.

2.7 Summary statistics

Table 2 reports summary statistics for the final sample. For comparison, the table also includes summary statistics for the sample of restaurants matched to corporate records but not matched to voter registration and Yelp. As can be seen from the table, firms in the voter registration sample are quite similar to firms in the full sample based on restaurant seats, age, and whether they have secured loans with banks and nonbanks. They also get PPP loans at roughly similar rates. Thus, restricting the analysis to firms we can match to the voter registration and Yelp samples does not seem to materially affect the types of firms we are studying.

Table 2
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, whose owner's race can be identified using Florida voter registration data, and that are matched to Yelp. Hotel and franchise restaurants are excluded.

	Final sample ($N = 9,980$)				Corporate records ($N = 21,761$)			
	Mean	SD	25th	75th	Mean	SD	25th	75th
Number of seats	87.97	103.44	35.00	135.00	86.94	101.16	30.00	130.00
Firm age	9.89	9.39	3.14	13.72	9.16	9.51	2.79	12.43
Bank UCC	0.16	0.37	0.00	0.00	0.15	0.36	0.00	0.00
Nonbank UCC	0.13	0.34	0.00	0.00	0.14	0.34	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	0.48	0.00	1.00
Bank PPP (2020)	0.64	0.48	0.00	1.00	0.58	0.49	0.00	1.00
Nonbank PPP (2020)	0.07	0.25	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

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

3 Documenting Disparities

Table 3 reports data on restaurant characteristics, locations, and emergency loan utilization for restaurants owned by the various 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 30% as likely to have a secured loan with a bank (6% vs. 20%). The means for the Yelp variables are fairly similar across demographic groups except for Black-owned restaurants, which have significantly fewer reviews, page views and photos, although the average rating of Black-owned restaurants is similar to those of other groups. Like other demographic groups, almost all Black-owned restaurants accept credit cards.

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 about 40% fewer branches per capita, 5% lower median household income, and 16% higher COVID cases per capita. Our regressions specifications will account for these geographic differences by comparing white- and minority-owned restaurants located in the same ZIP code.

Table 3 also shows that there are significant differences across groups in their use of emergency loans. 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 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.

For the other demographic groups we consider, the pattern of outcomes is generally in between those 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.

These differences are reflected in Table 4, which reports the results of linear probability model regressions of the various 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

Table 3
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, whose owner's race can be identified using Florida voter registration data, and that are matched to Yelp. Hotel and franchise restaurants are excluded.

		Race/Ethnicity				Gender	
	Total	White	Black	Asian	Hispanic	Male	Female
N	9,980	6,434	392	1,057	393	7,163	2,817
Firm characteristics							
Firm age	9.89	10.77	6.70	7.79	8.83	10.04	9.51
Num. seats	87.97	98.24	49.27	66.67	73.20	94.59	71.15
Bank UCC	0.16	0.20	0.06	0.08	0.12	0.18	0.12
Nonbank UCC	0.13	0.14	0.14	0.09	0.14	0.14	0.11
Accepts credit cards	0.99	0.98	0.98	1.00	0.99	0.99	0.98
Number of reviews	125.44	133.84	45.28	114.66	117.08	133.11	105.92
No reviews	0.06	0.05	0.19	0.04	0.08	0.06	0.06
Average rating	3.89	3.89	3.85	3.89	3.90	3.87	3.94
Page views	378.25	390.53	193.77	406.20	351.73	400.20	322.42
Photos	2.70	2.63	1.51	3.06	2.86	2.86	2.28
ZIP characteristics							
Population (000)	30.30	27.21	37.64	34.44	37.33	30.27	30.40
White population share	0.78	0.81	0.56	0.76	0.77	0.79	0.78
Bank branches per capita	0.38	0.41	0.23	0.37	0.34	0.39	0.37
Median household income (000)	60.27	61.58	49.88	62.09	56.86	60.83	58.85
COVID cases per capita	0.07	0.06	0.07	0.06	0.09	0.07	0.07
Outcomes							
Received PPP	0.70	0.74	0.48	0.71	0.64	0.72	0.67
Bank	0.64	0.69	0.34	0.58	0.58	0.66	0.59
Nonbank	0.07	0.05	0.14	0.13	0.06	0.06	0.08
EIDL	0.36	0.34	0.39	0.37	0.42	0.36	0.35
EIDL and PPP	0.29	0.29	0.23	0.31	0.31	0.30	0.27
EIDL, not PPP	0.06	0.05	0.16	0.06	0.10	0.06	0.08
No loans	0.23	0.22	0.36	0.23	0.26	0.22	0.25

firm f. A given firm can own multiple restaurants. Table 9 shows the robustness of our results to analyzing single-restaurant firms, which account for more than 90% of our sample.

In columns 1–4 of Panel A in Table 4 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, while excluding white restaurant-owner dummies, so we are measuring the likelihood that minority- and female-owned restaurants get a PPP loan relative to restaurants owned by white males. As shown in the first column, which reports the results for the regression without any controls, Black-owned restaurants are 25.0% less likely than white-owned restaurants to receive a PPP loan, while Hispanic-owned restaurants are 9.1% less likely. Both coefficients are statistically significant. Asian-owned restaurants are 2.2% less likely to receive a PPP loan although the difference is not statistically significant, while restaurants owned by women are 4.2% less likely to receive a PPP loan.

One reason why minority-owned restaurants may be less likely to receive PPP loans is that they are located in under-served banking markets (Wang and Zhang, 2020). The second column of Table 4 adds bank branch density to the regression. We also include population and median household income in 2019, as well as COVID cases per capita in 2020. All continuous variables are standardized to have a mean of zero and a standard deviation of one. Restaurants in ZIP codes with greater branch density are more likely to receive PPP loans. A one standard deviation increase in branch density increases the probability of receiving a PPP loan by only 2.5%. Given that only 30% of restaurants do not receive a PPP loan, the increase is meaningful. While the coefficient of the population variable is statistically insignificant, restaurants in ZIP codes with larger median income and fewer COVID cases per capita were also more likely to receive PPP funding. It is possible that restaurants in more affluent locations with fewer COVID cases were hit less hard by the pandemic and thus were more likely to survive and apply for PPP loans. Given that Black-owned restaurants are more likely to be in ZIP codes with low branch density, lower household income and more COVID cases per capita, the estimated magnitude of the coefficient of Black declines, but the reduction is just 4 percentage points, from 25.0% to 21.0%. The controls have a similar effect on the estimated disparity for Hispanic-owned restaurants.

Replacing these ZIP code level variables with ZIP code fixed effects in column 3 has a modest incremental effect on the estimated coefficients, reducing estimated disparities in PPP loans for Black-owned restaurants from 21.0% with controls to 19.8% with fixed effects. There is a similar modest impact on estimated disparities for Hispanic-owned restaurants, reducing the magnitude of coefficient from 6.8% to 6.3%. Thus, a combination of bank branch density, household income, and COVID cases per capita does a good job explaining variation in disparities across ZIP codes. Nevertheless, disparities for Black-owned restaurants remain large and statistically significant despite the inclusion of ZIP code fixed effects. The estimates for Hispanic-owned restaurants are smaller but still statistically significant.

Table 4
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, whose owner's race can be identified using Florida voter registration data, and that are matched to Yelp. Hotel and franchise restaurants are excluded. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Continuous variables are standardized so that their coefficients represent the effect of a one standard deviation change. $N = 9,980$.

Panel A: PPP and Bank PPP								
	PPP				Bank PPP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	-0.250^{***}	-0.210^{***}	-0.198^{***}	-0.098^{***}	-0.336^{***}	-0.293^{***}	-0.270^{***}	-0.166^{***}
	(0.026)	(0.026)	(0.029)	(0.028)	(0.025)	(0.025)	(0.028)	(0.027)
Hispanic	-0.091^{***}	-0.068^{***}	-0.063^{***}	-0.032^{**}	-0.099^{***}	-0.074^{***}	-0.068^{***}	-0.035^{**}
	(0.013)	(0.014)	(0.015)	(0.015)	(0.013)	(0.014)	(0.016)	(0.015)
Asian	-0.022	-0.018	-0.014	0.007	-0.103^{***}	-0.098^{***}	-0.092^{***}	-0.067^{***}
	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
Other	-0.042^{*}	-0.032	-0.026	-0.011	-0.082^{***}	-0.071^{***}	-0.061^{**}	-0.043^{*}
	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)	(0.026)
Female	-0.042^{***}	-0.038^{***}	-0.030^{***}	-0.007	-0.054^{***}	-0.049^{***}	-0.042^{***}	-0.017
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Bank branches per capita		0.025^{***}				0.032^{***}		
		(0.005)				(0.005)		
Ln(Population)		-0.007				-0.006		
		(0.006)				(0.006)		
Ln(Household income)		0.038^{***}				0.039^{***}		
		(0.005)				(0.005)		
COVID cases per capita		-0.013^{*}				-0.012		
		(0.007)				(0.008)		
Log(Number of seats)				0.049^{***}				0.055^{***}
				(0.005)				(0.006)
Ln(Firm age)				0.036^{***}				0.043^{***}
				(0.005)				(0.005)
Accepts credit cards				0.188^{***}				0.161^{***}
				(0.041)				(0.041)
Missing credit cards				-0.012				-0.007
				(0.021)				(0.021)
Ln(Reviews)				0.046^{***}				0.046^{***}
				(0.010)				(0.010)
Average rating				-0.021^{**}				-0.015
				(0.010)				(0.010)
No reviews				-0.154^{***}				-0.119^{***}
				(0.044)				(0.045)
Ln(Page views)				0.001				-0.007
				(0.011)				(0.012)
Ln(Photos)				0.040^{***}				0.052^{***}
				(0.007)				(0.008)
R^2	0.018	0.030	0.119	0.179	0.028	0.042	0.131	0.191
ZIP FEs			✓	✓			✓	✓

Continued

Table 4—*continued*

Panel B: Nonbank PPP and EIDL								
	Nonbank PPP				EIDL			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	0.086***	0.083***	0.072***	0.067***	0.049*	0.051**	0.042	0.054*
	(0.018)	(0.018)	(0.019)	(0.019)	(0.025)	(0.026)	(0.029)	(0.029)
Hispanic	0.008	0.006	0.005	0.003	0.079***	0.065***	0.042***	0.042***
	(0.006)	(0.007)	(0.008)	(0.008)	(0.013)	(0.014)	(0.016)	(0.016)
Asian	0.081***	0.081***	0.079***	0.074***	0.031*	0.024	0.015	0.014
	(0.011)	(0.011)	(0.011)	(0.011)	(0.016)	(0.016)	(0.017)	(0.018)
Other	0.040***	0.039***	0.035**	0.032**	0.062**	0.059**	0.048*	0.047*
	(0.015)	(0.015)	(0.015)	(0.015)	(0.025)	(0.026)	(0.027)	(0.027)
Female	0.012**	0.011*	0.012**	0.010*	−0.020*	−0.017	−0.007	−0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)	(0.011)	(0.011)
Bank branches per capita		−0.007***				0.021***		
		(0.003)				(0.006)		
Ln(Population)		−0.001				0.018***		
		(0.003)				(0.006)		
Ln(Household income)		−0.001				0.008		
		(0.003)				(0.005)		
COVID cases per capita		−0.001				0.026***		
		(0.004)				(0.007)		
Log(Number of seats)				−0.006*				0.012**
				(0.003)				(0.006)
Ln(Firm age)				−0.008***				−0.014**
				(0.003)				(0.005)
Accepts credit cards				0.028				0.088**
				(0.017)				(0.038)
Missing credit cards				−0.005				−0.007
				(0.011)				(0.022)
Ln(Reviews)				−0.000				0.013
				(0.005)				(0.011)
Average rating				−0.007				0.032***
				(0.006)				(0.010)
No reviews				−0.035				0.103**
				(0.024)				(0.045)
Ln(Page views)				0.008				0.003
				(0.006)				(0.012)
Ln(Photos)				−0.012***				−0.005
				(0.004)				(0.008)
R^2	0.015	0.015	0.107	0.109	0.004	0.008	0.097	0.100
ZIP FEs			✓	✓			✓	✓

In column 4, we add controls for firm age and size, using the log number of restaurant seats as a proxy for size. We also add a variety of restaurant characteristics from Yelp, all measured pre-pandemic. Larger and older restaurants are significantly more likely to receive PPP loans, as are those that accept credit cards and have more Yelp customer reviews and posted photos. These variables presumably measure how well established and popular the restaurant was prior to the pandemic. There are two reasons to include these controls. The first is that these characteristics could help control for PPP loan demand if smaller, less established and less popular restaurants were less profitable and thus more likely to shut down during the pandemic and not apply for a PPP loan as a result. The second is that these characteristics could control for loan supply as larger, more established and popular restaurants may have been prioritized by PPP lenders. This could be because they were more likely to be existing customers of the lender. It is also possible they were prioritized because there were more fees to be earned from making larger PPP loans or because these restaurants were more likely to ultimately survive and become future customers of the lender. Importantly, controlling for these firm characteristics reduces the magnitude of the coefficients on Black- and Hispanic-owned restaurants by about half—from 19.8 to 9.8% for Black-owned restaurants and from 6.3% to 3.2% for Hispanic-owned restaurants, both of which are still statistically significant. With the full set of controls there are no statistically significant disparities for Asian- and female-owned restaurants.

Next, we estimate separate regressions for bank and nonbank PPP lenders, with bank results reported in columns 5–8 of Panel A and nonbank results reported in columns 1–4 of Panel B. The findings indicate that the lower rate of PPP borrowing by Black- and Hispanic-owned restaurants is driven by bank lending. As shown in column 5 of Panel A, Black-owned restaurants are 33.6% less likely than white-owned restaurants to receive PPP funding from a bank. Adding controls in column 6, ZIP code fixed effects in column 7 and then restaurant characteristics in column 8 reduces the magnitude of the disparity in half to 16.6%, but it remains large and statistically significant. For Hispanic-owned restaurants, the difference is 3.5%, and Asian-owned restaurants—which showed no difference in overall PPP utilization—are 6.7% less likely to receive a bank PPP loan. There is no statistically significant difference for female-owned restaurants.

Columns 1–4 of Panel B in Table 4 tell a very different story 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 4, which include ZIP code fixed effects and restaurant characteristics, indicate that Black-owned restaurants are 6.7% more likely to receive a nonbank PPP loan and Asian-owned restaurants are 7.4% more likely to receive a nonbank PPP loan. The higher take-up rate of nonbank PPP loans by Black- and Asian-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. Note that the substitution to nonbank PPP loans is large enough for Asian-owned restaurants to fully offset their lower rate of borrowing from banks, but that this is not the case for Black-owned restaurants, which have lower rates of overall PPP utilization. The restaurants controls also indicate that smaller and younger restaurants substitute away from banks, which tend tend to lend more to larger and older firms.

In columns 5–8 of Panel B, we present results on the determinants of EIDL loans to restaurants. 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 8 regression, which includes controls for location and restaurant characteristics, Black-owned restaurants are 5.4% more likely than white-owned restaurants to receive EIDL loans, though the difference is only statistically significant at the 10% level. Hispanic-owned restaurants are 4.2% more likely than white-owned restaurants to receive loans from EIDL, which is statistically significant.

The fact that minority-owned restaurants apply for emergency loans from nonbanks and the EIDL program suggests that lower demand for emergency loans by minority restaurant-owners 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 evident demand for emergency loans, we can ask whether minority- and female-owned firms were less likely to receive bank PPP loans.

Table 5
Demand for Credit

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

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

where f indexes firms, r indexes restaurants, and z indexes ZIP codes. The sample consists of restaurants that receive either PPP or EIDL loans. Controls include all restaurant characteristics included in the regression in column 2 of Table 6. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Continuous variables are standardized so that their coefficients represent the effect of a one standard deviation change. $N = 7,676$.

	PPP			Bank PPP		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.180^{***}	-0.145^{***}	-0.102^{***}	-0.330^{***}	-0.275^{***}	-0.217^{***}
	(0.027)	(0.030)	(0.029)	(0.032)	(0.035)	(0.034)
Hispanic	-0.074^{***}	-0.058^{***}	-0.051^{***}	-0.088^{***}	-0.067^{***}	-0.055^{***}
	(0.010)	(0.011)	(0.011)	(0.012)	(0.014)	(0.014)
Asian	-0.014	-0.010	-0.004	-0.120^{***}	-0.114^{***}	-0.098^{***}
	(0.010)	(0.011)	(0.011)	(0.016)	(0.017)	(0.017)
Other	-0.047^{***}	-0.036^{*}	-0.028	-0.099^{***}	-0.083^{***}	-0.070^{***}
	(0.018)	(0.019)	(0.019)	(0.024)	(0.025)	(0.024)
Female	-0.023^{***}	-0.023^{***}	-0.011	-0.041^{***}	-0.039^{***}	-0.023^{**}
	(0.008)	(0.008)	(0.008)	(0.010)	(0.011)	(0.010)
R^2	0.023	0.145	0.183	0.040	0.161	0.197
ZIP FEs		✓	✓		✓	✓
Controls			✓			✓

In Table 5, we find that there are still disparities in PPP loans within this subsample of firms that received some type of emergency loan. Black- and Hispanic-owned restaurants are less likely to receive PPP loans. As before, the disparities are driven by disparities in bank lending. Banks are less likely to lend to all demographic groups even controlling for ZIP code and restaurant characteristics. In particular, Black-owned restaurants receiving some type of emergency loan are 21.7% less likely than white-owned restaurants to receive a loan from banks. Thus, differences across groups in loan demand do not seem to explain disparities in PPP lending. Rather these differences are likely 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; Fairlie, Robb, and Robinson, 2020). 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 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. 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 a firm has a bank loan outstanding. Although we cannot observe all of a firm's loans, we can observe 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 Uniform Commercial Code (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 February 15, 2020. As shown in Table 3, 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. In particular, only 6% of Black-owned restaurants have outstanding UCC loans from banks, while 20% of white-owned restaurants have such loans.

The dependent variable in the first three columns of Table 6 Panel A is whether the restaurant receives a PPP loan. In columns 4–6 we present regression results for bank PPP loans. In Panel B of the table we present results for nonbank PPP loans (columns 1–3) and EIDL loans (columns 4-6). The first column in each block of regressions (PPP, bank PPP, nonbank PPP, EIDL) repeats the baseline specifications from columns 4 and 8 of both panels in Table 4. The other columns add controls for whether the firm has an active bank or nonbank UCC loan and interaction terms described below. All regressions include ZIP code fixed effects and the full set of restaurant characteristics from Table 4 although they are not shown.

The results reported in column 2 indicate that having a bank UCC loan is associated with a 5.3% higher probability of receiving a PPP loan. Having a nonbank UCC loan increases the probability of receiving a PPP loan by 5.4%, which is also statistically significant. These effects are fairly large. Given that only 30% of restaurants do not receive PPP loans, a 5.3% increase in the probability of receiving a PPP loan reduces this probability by about 18%, a meaningful effect.

Controlling for secured lending relationships has no effect on the coefficient estimates of the minority restaurant-owner dummies. Black-owned restaurants are still 9.9% less likely than white-owned restaurants to receive a PPP loan even after controlling for existing UCC loans.

It is not surprising, given these results, that UCC lending relationships increase the likelihood of receiving a bank PPP loan. Restaurants are 7.7% more likely to receive a bank PPP loan if they have an outstanding bank UCC loan and 2.4% more likely to receive a bank PPP loan if they have an outstanding nonbank UCC loan. As in the overall PPP regressions, the inclusion of the UCC loan controls has a very modest effect on the coefficients of the minority-owned restaurant dummies and almost no effect on the Black-owned restaurant dummy.

The effect on estimated disparities in bank PPP lending is 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 7.7% (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 0.77%; in fact, it falls by only 0.2%.

Table 6
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. Controls include all restaurant characteristics included in the regression in column 2 of Table 6. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Continuous variables are standardized so that their coefficients represent the effect of a one standard deviation change. $N = 9,980$.

Panel A: PPP and Bank PPP						
	PPP			Bank PPP		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.098^{***}	-0.099^{***}	-0.070^{**}	-0.166^{***}	-0.164^{***}	-0.145^{***}
	(0.028)	(0.028)	(0.031)	(0.027)	(0.027)	(0.029)
Hispanic	-0.032^{**}	-0.030^{**}	-0.029^{*}	-0.035^{**}	-0.032^{**}	-0.032^{*}
	(0.015)	(0.015)	(0.017)	(0.015)	(0.015)	(0.017)
Asian	0.007	0.014	0.013	-0.067^{***}	-0.059^{***}	-0.063^{***}
	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.019)
Other	-0.011	-0.007	0.011	-0.043^{*}	-0.040	-0.025
	(0.025)	(0.025)	(0.028)	(0.026)	(0.026)	(0.029)
Female	-0.007	-0.005	-0.008	-0.017	-0.015	-0.012
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)
Bank UCC loan		0.053^{***}	0.080^{***}		0.077^{***}	0.114^{***}
		(0.012)	(0.016)		(0.013)	(0.017)
Nonbank UCC loan		0.054^{***}	0.076^{***}		0.024^{*}	0.033^{*}
		(0.012)	(0.017)		(0.014)	(0.019)
Black × Bank UCC loan			-0.181^{*}			-0.251^{**}
			(0.099)			(0.098)
Black × Nonbank UCC loan			-0.096			0.017
			(0.076)			(0.079)
R^2	0.179	0.183	0.188	0.191	0.195	0.199

Panel B: Nonbank PPP and EIDL						
	Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.067^{***}	0.065^{***}	0.075^{***}	0.054^{*}	0.050^{*}	0.050
	(0.019)	(0.019)	(0.021)	(0.029)	(0.029)	(0.031)
Hispanic	0.003	0.002	0.003	0.042^{***}	0.043^{***}	0.040^{**}
	(0.008)	(0.008)	(0.008)	(0.016)	(0.016)	(0.017)
Asian	0.074^{***}	0.074^{***}	0.076^{***}	0.014	0.023	0.013
	(0.011)	(0.011)	(0.012)	(0.018)	(0.018)	(0.019)
Other	0.032^{**}	0.033^{**}	0.036^{**}	0.047^{*}	0.052^{*}	0.054^{*}
	(0.015)	(0.015)	(0.017)	(0.027)	(0.027)	(0.030)
Female	0.010^{*}	0.010	0.005	-0.005	-0.002	0.004
	(0.006)	(0.006)	(0.007)	(0.011)	(0.011)	(0.013)
Bank UCC loan		-0.024^{***}	-0.033^{***}		0.054^{***}	0.045^{**}
		(0.006)	(0.008)		(0.014)	(0.020)
Nonbank UCC loan		0.030^{***}	0.043^{***}		0.108^{***}	0.143^{***}
		(0.008)	(0.012)		(0.015)	(0.022)
Black × Bank UCC loan			0.070			0.165
			(0.076)			(0.123)
Black × Nonbank UCC loan			-0.112^{**}			-0.083
			(0.046)			(0.083)
R^2	0.109	0.112	0.115	0.100	0.107	0.110
ZIP FEs	✓	✓	✓	✓	✓	✓
Controls		✓	✓		✓	✓
Controls × UCC			✓			✓

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 looked at the PPP lending intensity of banks having secured lending relationships with white- versus minority-owned restaurants. We include all Florida-based firms that had an active UCC lending relationship with a bank as of February 15, 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 a 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 Table 6 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 6. These estimates are available in the Appendix Table A5.) 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. In the bank PPP regression shown in column 6, 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 25.1% less for Black-owned restaurants than for white-owned restaurants. Given that white-owned restaurants with outstanding bank loans are 11.4% 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 13.7% less likely than those without them to get bank PPP loans, although this effect is estimated with considerable noise and is thus 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 lending relationships 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 1–3 of Table 6 Panel B report the results for nonbank PPP loans. The coefficient on the bank UCC loan variable in column 2 is -2.4% while the coefficient on the nonbank UCC loan variable is 3.0%. 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 fact that restaurants with prior nonbank loans are more likely to receive nonbank PPP loans suggests that these nonbank relationships also confer advantages in receiving PPP loans. The coefficients of the interaction terms are reported in column 3. While not statistically significant, the positive coefficient on the bank UCC loan variable indicates that Black-owned restaurants with these outstanding loans are more likely to apply for nonbank PPP loans, consistent with the finding that they are less likely to receive for bank PPP loans. These results also indicate that Black-owned restaurants with nonbank UCC loans are less likely to apply for nonbank PPP loans suggesting that nonbank lending relationships, like bank lending relationships, confer less advantage to Black-owned restaurants. It is also possible 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 4–6 of Panel B examine the effect of lending relationships on EIDL loans. In column 5 the coefficients on bank and nonbank UCC loans are positive and highly statistically significant. 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. Neither interaction term is statistically significant.

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 and they do not increase the overall likelihood that Black-owned restaurants received PPP funding. 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 lenders 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 PPP loans in locations with more racial bias among the white population. We use data on explicit and implicit racial bias collected by Project Implicit[15]. Project Implicit offers a number of online implicit association tests 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

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

for white over Black people.[16] 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."

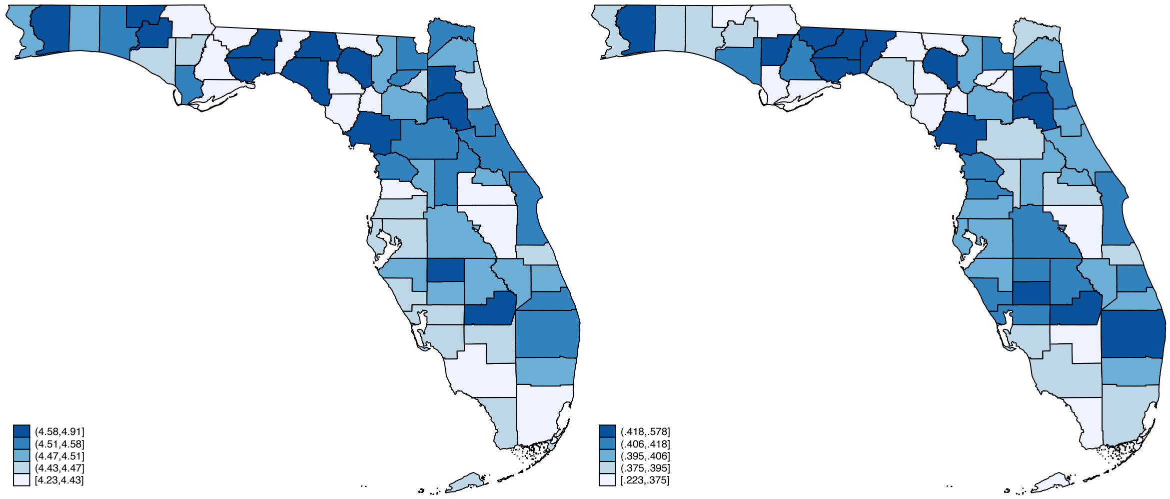
Implicit bias has been shown to be associated with discriminatory behavior. Glover, Pallais, and Pariente (2017) show that implicit bias of grocery store managers affects the performance of minority cashiers. On days when they are supervised by biased managers, minority cashiers are more likely to be 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, just 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 7 reports the results of linear probability models for PPP loans and bank PPP loans in Panel A, and nonbank PPP loans and EIDL loans in Panel B. 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. County-level 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 in a county 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. All regressions include restaurant characteristics and UCC loans although their estimated coefficients are not reported.

In columns 1 and 2 we examine whether minority-owned restaurants located in more racially biased counties are less likely to receive PPP loans. In both regressions, the interaction term between *Black* and *Bias* is small, positive and statistically insignificant. The coefficient on *Black* is still negative, indicating that while the average Black-owned restaurant is less likely to receive a

[16] 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.

PPP loan, this disparity is not greater in more racially biased counties.

In columns 3 and 4, we examine the effect of racial bias on the probability of receiving a bank PPP loan. In both regressions, the interaction between *Bias* and *Black* is negative and statistically significant. The magnitude of the effect is very large. A one standard deviation increase in racial bias is associated with 13.9%–15.1% reduction in the probability that a Black-owned restaurant receives a bank PPP loan, depending on whether we use explicit or implicit bias as the measure. Given that Black-owned restaurants are 22.3% (16.8%) less likely get a bank PPP loan in a county with average explicit (implicit) bias, this implies that Black-owned restaurants are 36.2% (31.9%) less likely to receive bank PPP funding in counties with explicit (implicit) bias one standard deviation above the mean.[17] 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 towards Black people may be correlated with bias against other minority groups, its strongest effect is on the likelihood that Black-owned restaurants receive bank PPP loans.

In columns 5 and 6, we present results for nonbank PPP loans. Here the coefficient on the

[17] 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 7
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. Regressions are weighted by the number of white respondents to the Race Implicit Association Test during 2008–2019 period. Controls include all restaurant characteristics included in the regression in column 2 of Table 6. Standard errors are adjusted for clustering by county. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Continuous variables are standardized so that their coefficients represent the effect of a one standard deviation change. $N = 9,980$.

	PPP		Bank PPP		Nonbank PPP		EIDL	
	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	−0.105	−0.119**	−0.223***	−0.168***	0.118***	0.049	0.061	0.018
	(0.065)	(0.046)	(0.038)	(0.024)	(0.037)	(0.034)	(0.043)	(0.034)
Hispanic	−0.056**	−0.034**	−0.038	−0.022	−0.017***	−0.012**	0.066**	0.063***
	(0.022)	(0.015)	(0.024)	(0.019)	(0.006)	(0.006)	(0.031)	(0.017)
Asian	0.008	0.003	−0.081***	−0.055***	0.090***	0.058***	0.014	0.004
	(0.020)	(0.012)	(0.027)	(0.021)	(0.013)	(0.011)	(0.030)	(0.036)
Other	−0.083***	0.002	−0.093***	−0.033	0.010	0.035	0.053*	0.053**
	(0.029)	(0.023)	(0.030)	(0.027)	(0.016)	(0.023)	(0.030)	(0.022)
Female	−0.008	−0.010	−0.035***	−0.026***	0.027**	0.017**	−0.009	−0.003
	(0.008)	(0.008)	(0.010)	(0.007)	(0.011)	(0.008)	(0.016)	(0.011)
Black × Bias	0.030	0.062	−0.139*	−0.151**	0.169**	0.213**	0.098	0.175*
	(0.131)	(0.106)	(0.070)	(0.063)	(0.075)	(0.091)	(0.098)	(0.099)
Hispanic × Bias	−0.056	−0.088	−0.045	−0.079	−0.011	−0.009	0.008	0.030
	(0.052)	(0.056)	(0.062)	(0.069)	(0.014)	(0.016)	(0.039)	(0.038)
Asian × Bias	0.012	0.051	−0.064	−0.046	0.076**	0.097*	0.023	0.021
	(0.033)	(0.044)	(0.057)	(0.091)	(0.031)	(0.049)	(0.084)	(0.099)
Other × Bias	−0.213***	−0.253***	−0.147	−0.215**	−0.066	−0.038	−0.002	0.018
	(0.054)	(0.086)	(0.089)	(0.097)	(0.060)	(0.082)	(0.050)	(0.085)
Female × Bias	0.004	0.003	−0.021	−0.025**	0.024*	0.028	−0.014	−0.032
	(0.016)	(0.018)	(0.013)	(0.012)	(0.014)	(0.018)	(0.023)	(0.023)
R^2	0.170	0.170	0.180	0.180	0.103	0.103	0.097	0.097
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓

interaction between *Black* and *Bias* is 16.9%–21.3% and statistically significant, the opposite of the sign for bank PPP loans. These results suggest that Black-owned restaurants are more likely to substitute from bank to nonbank PPP loans in counties with greater racial bias. In fact, the extent of substitution is so strong in more racially biased counties that it fully offsets the lower levels of bank PPP lending in these counties, which is why the interaction terms in columns 1 and 2 are essentially zero. Note, however, that in the average county there are still disparities between Black- and white-owned restaurants in access to PPP.

Finally in columns 7 and 8, the dependent variable is whether the firm receives an EIDL loan. As with nonbank PPP loans, we find a positive interaction between *Black* and *Bias*, suggesting more substitution to EIDL loans in more biased counties. However, only the interaction with implicit bias is statistically significant at the 10% level.

One may be concerned that racial bias is correlated with other county-level characteristics such as white population share, personal income, and unemployment, in a way that may explain differences in take-up rates and drive the results in Table 7. Table A3 in the Appendix addresses this concern by adding interactions of *Black* with various county-level characteristics. The results indicate that the basic conclusions in Table 7 are robust to the inclusion of county characteristics. Bank PPP loans to Black-owned restaurants are considerably lower in more racially biased counties and nonbank PPP loans substitute for bank loans in these counties.[18]

As a check on the validity of this general approach to measuring bias, we examine whether implicit bias with respect to gender is associated with lower utilization of bank PPP loans by female-owned restaurants. Specifically, we use the results of the Gender-Career Implicit Association Test, which measures the extent to which test-takers associate women with staying at home to take care of the family as opposed to pursuing a career. Appendix Table A4 shows that female-owned restaurants are less likely to receive bank PPP loans in counties where people do not associate women with having a career. The table also shows that in these more gender-biased counties female-owned restaurants are more likely to tap nonbank sources of PPP loans. The results provide further support for the idea that the racial bias measure is indeed measuring a sentiment that would affect the take-up of bank PPP loans by Black-owned businesses.

Finally, we study whether racial disparities were attenuated in the third round of PPP, which began on January 11, 2021. 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 this round. These include setting aside funds for the following: 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. In total, \$278 billion of loans were made in the third round of PPP. We explore whether the changes made in this round mitigated racial disparities in the program.

The results in Table 8, which use data running from January 12 through June 30, 2021, suggest that there was some attenuation in racial disparities in the case of Black-owned restaurants, particularly in more racially biased counties. Columns 1–2 report the results for PPP lending, columns 3–4 report the results for bank PPP lending, and columns 5–6 report the results for nonbank PPP loans. ZIP code fixed effects and restaurant characteristics are included in all the regressions.

Comparing the third columns of Table 8 and Table 7, both of which uses the explicit bias

[18] The one anomalous finding is that there is a large statistically significant negative interaction between *Black* and racial bias in the EIDL regressions (columns 7 and 8), whereas this interaction term is positive in Table 7 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.

Table 8
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. Controls include all restaurant characteristics included in the regression in column 2 of Table 6. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Continuous variables are standardized so that their coefficients represent the effect of a one standard deviation change. $N = 9,980$.

	PPP		Bank PPP		Nonbank PPP	
	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.050	−0.096***	−0.108***	−0.120***	0.058***	0.023*
	(0.036)	(0.023)	(0.035)	(0.021)	(0.015)	(0.012)
Hispanic	−0.042**	−0.035***	−0.050***	−0.033**	0.009	−0.002
	(0.018)	(0.013)	(0.016)	(0.015)	(0.014)	(0.009)
Asian	0.052**	0.024	−0.001	−0.024*	0.053***	0.048***
	(0.021)	(0.015)	(0.024)	(0.014)	(0.018)	(0.012)
Other	0.015	−0.027	−0.034*	−0.071***	0.049*	0.044**
	(0.030)	(0.026)	(0.020)	(0.017)	(0.028)	(0.020)
Female	−0.010	−0.026**	−0.032**	−0.037***	0.022***	0.011***
	(0.013)	(0.010)	(0.013)	(0.010)	(0.006)	(0.002)
Black × Bias	0.110*	0.165***	0.023	0.071	0.087***	0.094***
	(0.060)	(0.051)	(0.070)	(0.068)	(0.020)	(0.026)
Hispanic × Bias	−0.014	−0.019	−0.040	−0.046	0.026	0.027
	(0.042)	(0.047)	(0.040)	(0.044)	(0.018)	(0.027)
Asian × Bias	0.068	0.092**	0.057	0.096***	0.011	−0.004
	(0.042)	(0.035)	(0.038)	(0.032)	(0.021)	(0.022)
Other × Bias	0.105	0.109	0.093**	0.098**	0.012	0.010
	(0.072)	(0.090)	(0.044)	(0.044)	(0.045)	(0.060)
Female × Bias	0.038**	0.064***	0.012	0.028	0.026**	0.036***
	(0.019)	(0.020)	(0.021)	(0.022)	(0.011)	(0.009)
R^2	0.130	0.131	0.136	0.136	0.086	0.086
ZIP FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

measure, we see that Black-owned restaurants go from being 22.3% less likely to receive a bank PPP loan in the first two rounds of PPP to being 10.8% less likely to receive a bank PPP loan in the third round of PPP. The reduction in disparities is somewhat smaller using the implicit bias measure—a drop from 16.8% to 12.0%. For Black-owned restaurants in more racially biased counties one standard deviation above the mean, disparities in bank PPP lending fall even more given that the estimated interaction term is slightly positive in the third round and not statistically significant. Moreover, given that racial disparities in bank PPP lending fall, there is somewhat weaker substitution to nonbank PPP loans, particularly in more racially biased counties as shown in columns 5 and 6 of the table. Finally, overall disparities in PPP lending fall as seen in columns 1 and 2. In fact, PPP loans to Black-owned restaurants are even greater in more racially biased counties, perhaps because of the measures taken in round 3 to enhance access to under-served businesses in those location in the first two rounds.

6 Robustness and External Validity

6.1 Robustness

Our analysis so far includes detailed information on restaurant characteristics from restaurant licenses and Yelp. Including these characteristics in the regressions helps to explain variation in bank PPP loans, and significantly reduces estimated disparities. For a somewhat smaller sample of restaurants we have additional data that could help to explain PPP loans and further reduce estimated disparities. In particular, we use data from SafeGraph and Dun & Bradstreet as an additional set of controls in our regressions.

SafeGraph collects anonymous data on visits to different points of interest using cell phone tracking.[19] We use the average number of monthly visits to the restaurant, which could crudely proxy for pre-pandemic profitability when also controlling for restaurant size. We also match our sample of restaurants to Dun & Bradstreet, which has information on the number of employees.

The results in Table 9 indicate that restaurants that had more pre-pandemic visits were more likely to receive bank PPP funding (column 2). In addition, restaurants with more employees as estimated by Dun & Bradstreet were more likely to receive bank PPP funding (column 3). These effects are statistically significant but moderate in magnitude. A one standard deviation increase in restaurant visits increases the probability of receiving a PPP loan by about 1.2%, while a one standard deviation increase in employees increases the probability by 1.8%. More importantly, however, the estimated disparity in lending to Black-owned restaurants is not changed by the inclusion of these additional controls, as can be seen by comparing the coefficients to column 1 results without the additional Safegraph and D&B controls. However, the disparity in lending to Hispanic-owned restaurants shrinks with the inclusion of the SafeGraph and D&B controls, although this is because of the change in sample when we add these controls.

The remaining columns of Table 9 show the robustness of our results to a number of alternative specifications. In column 4, we restrict the sample to single-restaurant firms, which account for 93% of the sample.[20] We find very similar results. In column 5, 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.[21] We find somewhat stronger results when incorporating information about PPP loans received by affiliates. Finally, in columns

[19] 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.

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

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

Table 9
Robustness

This table shows the robustness of the results in Table 4 to additional controls and alternative specifications. Column 2 controls for the log of one plus the number of monthly visits as estimated by SafeGraph. Column 3 controls for the log of one plus the number of employees from D&B. Column 4 restricts the sample to single-restaurant firms. Column 5 classifies a firm as having received PPP loans if any of its affiliates receives PPP loans. Column 6 uses 4,183 Census block group instead of 820 ZIP code fixed effects. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Continuous variables are standardized so that their coefficients represent the effect of a one standard deviation change.

	Additional controls			Single restaurant firms	Loans to affiliates	Census block group
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: PPP						
Black	−0.099***	−0.098***	−0.095***	−0.088***	−0.125***	−0.080*
	(0.028)	(0.030)	(0.035)	(0.029)	(0.028)	(0.042)
Hispanic	−0.030**	−0.028*	−0.012	−0.037**	−0.047***	−0.001
	(0.015)	(0.016)	(0.018)	(0.015)	(0.014)	(0.020)
Asian	0.014	0.018	0.009	0.021	−0.001	0.023
	(0.016)	(0.017)	(0.019)	(0.016)	(0.015)	(0.023)
Other	−0.007	0.000	0.003	−0.016	−0.023	−0.017
	(0.025)	(0.026)	(0.030)	(0.025)	(0.024)	(0.036)
Female	−0.005	−0.007	−0.009	−0.006	−0.019*	0.001
	(0.011)	(0.011)	(0.013)	(0.011)	(0.010)	(0.015)
Ln(Monthly visits)		0.012**				
		(0.005)				
Ln(Employees)			0.018***			
			(0.006)			
N	9,980	8,801	6,978	9,271	9,980	9,980
R^2	0.183	0.194	0.208	0.192	0.192	0.501
Panel B: Bank PPP						
Black	−0.164***	−0.165***	−0.130***	−0.155***	−0.181***	−0.155***
	(0.027)	(0.029)	(0.035)	(0.028)	(0.027)	(0.040)
Hispanic	−0.032**	−0.028*	−0.004	−0.035**	−0.043***	−0.016
	(0.015)	(0.016)	(0.019)	(0.016)	(0.015)	(0.021)
Asian	−0.059***	−0.059***	−0.062***	−0.051***	−0.070***	−0.047*
	(0.017)	(0.018)	(0.020)	(0.018)	(0.017)	(0.025)
Other	−0.040	−0.019	−0.027	−0.039	−0.053**	−0.043
	(0.026)	(0.027)	(0.031)	(0.026)	(0.025)	(0.036)
Female	−0.015	−0.020*	−0.018	−0.014	−0.028***	−0.008
	(0.011)	(0.012)	(0.013)	(0.011)	(0.011)	(0.015)
Ln(Monthly visits)		0.018***				
		(0.005)				
Ln(Employees)			0.020***			
			(0.006)			
N	9,980	8,801	6,978	9,271	9,980	9,980
R^2	0.195	0.208	0.218	0.200	0.207	0.507
ZIP FEs	✓	✓	✓	✓	✓	
Controls	✓	✓	✓	✓	✓	✓
Census block group FEs						✓

6 we examine robustness to using fixed effects for Census block groups, a more granular geography than ZIP code. This regression is meant to address the concern that even within a ZIP code, minority-owned restaurants may be located farther away from bank branches or may be subject to different shocks. We obtain 2010 Census block information from the Census geocoder[22] and Texas A&M GeoServices.[23] 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. There are 820 ZIP codes and 4,183 Census block groups in the data. We find similar results when comparing minority- and white-owned restaurants within these more narrowly defined geographic areas.

6.2 Excluding closed restaurants

In our main analysis we control for potential differences in demand for PPP loans by controlling for an extensive set of restaurant characteristics and, in Table 5, by restricting the sample to firms that receive either PPP or EIDL loans. An alternative approach to control for demand is to exclude restaurants that closed since the start of the COVID-19 pandemic. These restaurants may have decided to shut down and not apply for PPP loans because, even if they received PPP loans and stayed open for a while longer, their long-term outlook was weak. Excluding closed restaurants, however, is an imperfect solution as some restaurants may have closed because they could not receive PPP loans to help them weather the pandemic. If minority-owned restaurants were more likely to close because of failure to receive PPP loans, then analyzing restaurants that are still open will understate the extent of racial disparities. With this in mind, Table 10 reports the results for the full sample as well as for the sample that excludes closed restaurants.

We consider a restaurant to have closed if one of the following three conditions is satisfied: 1) Yelp reports a valid permanent closure date; 2) restaurant license data indicate a change in ownership taking place after February 15, 2020; 3) the restaurant is not listed as active in the October 2021 restaurant licenses data. About 11% of restaurants in our data have permanently closed or changed ownership since the pandemic. Closed restaurants are 20% less likely to receive PPP loans and 4.7% less likely to receive EIDL loans than are restaurants that are still open.

The results are similar in the subsample of restaurants that are still active and the full sample of restaurants. This finding cuts against the hypothesis that we may observe disparities in PPP lending because minority-owned restaurants, facing weaker long-term prospects, are more likely to shut down and not apply for PPP loans. Comparing columns 1–2 of the table, we see that in the full sample Black-owned restaurants are 9.9% less likely to received PPP loans, while in the active subsample they are 12.2% less likely to receive PPP loans. We cannot reject the hypothesis that

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

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

Table 10
Robustness to Excluding Closed Restaurants

This table shows the robustness of the results in Table 6 to excluding restaurants that closed. A restaurant is considered to have closed if one of the following three conditions is satistifed: 1) Yelp reports a valid permanently closed date, 2) license data indicate a change in ownership after February 15, 2020, or 3) restaurant is not in the October 2021 snapshot of the active restaurant licenses. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	PPP		Bank PPP		Nonbank PPP		EIDL	
	All	Active	All	Active	All	Active	All	Active
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	-0.099^{***}	-0.122^{***}	-0.164^{***}	-0.167^{***}	0.065^{***}	0.045^{**}	0.050^{*}	0.042
	(0.028)	(0.031)	(0.027)	(0.031)	(0.019)	(0.020)	(0.029)	(0.032)
Hispanic	-0.030^{**}	-0.032^{**}	-0.032^{**}	-0.034^{**}	0.002	0.002	0.043^{***}	0.041^{**}
	(0.015)	(0.015)	(0.015)	(0.016)	(0.008)	(0.008)	(0.016)	(0.017)
Asian	0.014	0.009	-0.059^{***}	-0.070^{***}	0.074^{***}	0.080^{***}	0.023	0.015
	(0.016)	(0.017)	(0.017)	(0.018)	(0.011)	(0.012)	(0.018)	(0.019)
Other	−0.007	−0.016	−0.040	-0.053^{**}	0.033^{**}	0.037^{**}	0.052^{*}	0.038
	(0.025)	(0.026)	(0.026)	(0.027)	(0.015)	(0.016)	(0.027)	(0.028)
Female	−0.005	−0.006	−0.015	−0.019	0.010	0.012^{*}	−0.002	−0.014
	(0.011)	(0.011)	(0.011)	(0.012)	(0.006)	(0.006)	(0.011)	(0.012)
N	9,980	8,885	9,980	8,885	9,980	8,885	9,980	8,885
R^2	0.183	0.177	0.195	0.189	0.112	0.121	0.107	0.118
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓

these two estimates are the same. We find similar results for the other outcomes.

6.3 External validity

One may wonder whether there is something special about restaurants and thus 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. Since we cannot identify the population of potential borrowers in this broader sample of firms, we examine PPP utilization within the sample of firms that received emergency loans from PPP or EIDL. We ask whether minority-owned firms were less likely to receive PPP loans from any source and from banks in this sample of firms that received some form of emergency loan. This is the same basic approach we took in Table 5 to control for loan demand in the restaurant sample.

To create the broader sample, we start by matching PPP and EIDL borrowers to Florida corporate records, restricting the sample to Florida-based for-profit firms. Since there is likely to be significant variation in the share of minority-owned businesses in an industry, as well as variation in the use of emergency loans across industries, we control for industry in our analysis. 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 on the 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 11

External Validity: Utilization of PPP Loans

This table reports the results of linear probability model regressions of receiving 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%. Continuous variables are standardized so that their coefficients represent the effect of a one standard deviation change. $N = 131,465$.

	PPP				Bank PPP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	-0.294^{***}	-0.229^{***}	-0.210^{***}	-0.153^{***}	-0.389^{***}	-0.313^{***}	-0.294^{***}	-0.228^{***}
	(0.005)	(0.006)	(0.009)	(0.009)	(0.005)	(0.006)	(0.009)	(0.009)
Hispanic	-0.235^{***}	-0.167^{***}	-0.159^{***}	-0.122^{***}	-0.241^{***}	-0.172^{***}	-0.161^{***}	-0.120^{***}
	(0.003)	(0.004)	(0.006)	(0.006)	(0.003)	(0.004)	(0.007)	(0.007)
Asian	-0.022^{***}	-0.027^{***}	-0.030^{***}	-0.005	-0.055^{***}	-0.056^{***}	-0.063^{***}	-0.034^{***}
	(0.006)	(0.006)	(0.010)	(0.010)	(0.007)	(0.007)	(0.011)	(0.011)
Other	-0.108^{***}	-0.088^{***}	-0.091^{***}	-0.064^{***}	-0.127^{***}	-0.102^{***}	-0.113^{***}	-0.081^{***}
	(0.007)	(0.007)	(0.011)	(0.011)	(0.008)	(0.008)	(0.012)	(0.012)
Female	-0.019^{***}	-0.016^{***}	-0.017^{***}	-0.003	-0.027^{***}	-0.021^{***}	-0.022^{***}	-0.006
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)
Ln(Firm age)				0.062^{***}				0.069^{***}
				(0.003)				(0.003)
Ln(Sales)				0.056^{***}				0.056^{***}
				(0.004)				(0.004)
Ln(Employees)				-0.004				0.006
				(0.003)				(0.004)
Bank UCC loan				0.076^{***}				0.106^{***}
				(0.005)				(0.005)
Nonbank UCC loan				0.059^{***}				0.028^{***}
				(0.006)				(0.007)
R^2	0.065	0.142	0.521	0.545	0.073	0.150	0.529	0.557
ZIP FEs		✓				✓		
SIC FEs		✓				✓		
SIC-ZIP FEs			✓	✓			✓	✓

Table 11 examines whether there are disparities in PPP loans and bank PPP loans. Columns 1–4 examine the determinants of PPP loans overall, while columns 5–8 examine the determinants of bank PPP loans. The first column in each block of regressions estimates minority business-owner dummies without controls for location, industry and firm characteristics. The second column in each block adds ZIP code and industry fixed effects, while the the third column adds industry cross ZIP code fixed effects. Finally, the fourth column in each block adds firm age, sales and employees controls, as well as prior bank and nonbank UCC loans. These variables tell a familiar story: larger and older firms with a history of bank and nonbank borrowing are more likely to receive PPP loans from banks. As in the baseline regressions, adding controls reduces estimated disparities for both PPP and bank PPP loans but these disparities remain large and statistically significant for Black- and Hispanic-owned firms. Even with controls, Black-owned businesses are 15.3% less likely to receive PPP loans and 22.8% less likely to receive bank PPP loans. Hispanic-owned businesses are also 12.2% less likely to receive PPP loans, and 12.0% less likely to receive them from banks.

Table 12
External Validity: Racial Bias

This table reports the results of linear probability model regressions of receiving 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. Controls include log of firm age, log sales, log employees, bank UCC loans, and nonbank UCC loans. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. $N = 93,565$.

	PPP				Bank PPP			
	Explicit		Implicit		Explicit		Implicit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	−0.148***	−0.147***	−0.143***	−0.143***	−0.222***	−0.221***	−0.214***	−0.213***
	(0.019)	(0.018)	(0.022)	(0.021)	(0.013)	(0.012)	(0.020)	(0.017)
Hispanic	−0.120***	−0.121***	−0.124***	−0.122***	−0.117***	−0.118***	−0.123***	−0.119***
	(0.015)	(0.014)	(0.020)	(0.013)	(0.016)	(0.014)	(0.020)	(0.014)
Asian	−0.007	−0.005	−0.012	−0.005	−0.036***	−0.033***	−0.041***	−0.033***
	(0.012)	(0.011)	(0.018)	(0.011)	(0.011)	(0.011)	(0.013)	(0.011)
Other	−0.062***	−0.063***	−0.055***	−0.064***	−0.080***	−0.081***	−0.073***	−0.081***
	(0.012)	(0.013)	(0.015)	(0.013)	(0.018)	(0.018)	(0.023)	(0.018)
Female	−0.004	−0.003	−0.009	−0.003	−0.006	−0.006	−0.009	−0.006
	(0.006)	(0.006)	(0.008)	(0.006)	(0.004)	(0.005)	(0.007)	(0.005)
Black × Bias	−0.077*	−0.084**	−0.059	−0.059	−0.093*	−0.105***	−0.087	−0.093*
	(0.044)	(0.040)	(0.066)	(0.059)	(0.048)	(0.039)	(0.059)	(0.048)
Hispanic × Bias	0.037		0.023		0.052		0.039	
	(0.057)		(0.062)		(0.056)		(0.060)	
Asian × Bias	0.044		0.048		0.061		0.048	
	(0.053)		(0.059)		(0.039)		(0.041)	
Other × Bias	−0.049		−0.065		−0.036		−0.060	
	(0.057)		(0.076)		(0.071)		(0.099)	
Female × Bias	0.028		0.046*		0.023		0.023	
	(0.026)		(0.027)		(0.024)		(0.027)	
R^2	0.545	0.545	0.545	0.545	0.557	0.557	0.556	0.556
SIC-ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓

Table 12 examines whether disparities are greater in more racially biased counties along the lines of Table 7 for restaurants but in this broader sample of firms that take out emergency loans. All of the regressions include ZIP code cross industry fixed effects and the same controls as in Table 11. Our findings are broadly in line with the restaurant findings for both PPP loans and bank PPP loans. The interaction of *Black* and *Bias* is negative. As before, the effect is large and statistically significant for bank PPP loans. The effect is smaller for overall PPP loans, although still negative and in some specifications statistically significant. Our general conclusion is that our findings for restaurants are broadly applicable across a much wider range of industries.

7 Conclusion

We have documented racial disparities in the Paycheck Protection Program and examined their causes. About 60% of disparities for Black- and Hispanic-owned restaurants can be explained by a combination of location, restaurant characteristics, and past borrowing relationships. Black-owned restaurants are still 10% less likely to receive PPP funding than similar white-owned restaurants. For Hispanic-owned restaurants the difference is a more modest 3%, and for Asian-owned restaurants and female-owned restaurants there is no appreciable difference in PPP utilization.

Disparities in PPP loan utilization are driven by disparities in bank PPP lending. Black-owned restaurants are 16.6% less likely than white-owned restaurants to borrow from banks, while Hispanic-owned restaurants are 3.5% less likely, and Asian-owned restaurants are 6.7% less likely. Nonbanks—largely fintechs—make up for a portion of these disparities by lending at greater rates to Black-owned restaurants (6.7%) and they make up the entire difference for Asian-owned restaurants. Hispanic-owned restaurants borrow from nonbanks at the same rate as white-owned restaurants.

Our findings also speak to disparities in the value of bank relationships. While bank borrowing relationships increased the likelihood that white-owned businesses received bank PPP loans, this was not the case for Black-owned restaurants. Thus, Black-owned businesses may have suffered in two respects: their bank borrowing relationships did not result in greater PPP access and they were much less likely to have a bank borrowing relationship in the first place.

The disparities in bank PPP loans appear to be exacerbated by racial bias. Restaurants located in counties in which more white people express implicit or explicit biases towards Black people are less likely to receive PPP loans from banks and are more likely to substitute to nonbank PPP loans and EIDL loans. We see this basic pattern across a wide range of industries in Florida. Racial bias may have affected banks' administration of the PPP or it may have reflected a legacy of bias that deterred Black restaurant owners from applying for PPP loans from banks. Our methodology cannot tell apart these two explanations, but our findings do suggest that online, less personalized applications can help to mitigate bias. Both fintechs, in originating PPP loans, and the SBA, in originating EIDL loans, used an online application process with relatively less personal interaction than was the case for many banks.

Remaining disparities in PPP utilization by Black-owned restaurants do not appear to be driven by lower demand for PPP loans given: 1) extensive controls for location, restaurant characteristics and past borrowing behavior; 2) the fact that Black-owned restaurants are less likely to receive bank PPP loans even when they apply for loans from PPP or the EIDL program; and 3) disparities are greater in more racially biased counties.

Our findings also point to potential issues with the design of PPP that may have inadvertently affected the access of minority-owned businesses to PPP loans. While our focus has been on understanding racial disparities once we control for location, restaurant characteristics and past borrowing relationships, it is worth noting that minority-owned businesses tend be located in areas with lower PPP take-up rates, are more likely to have characteristics of restaurants with low take-up rates, and lack the borrowing relationships that increased PPP take-up rates. These factors explain 60% of the disparities in lending to Black- and Hispanic-owned businesses. While it is possible that some of these factors may have lowered restaurant demand for PPP loans, it is also possible that some of these factors—such as proximity to bank branches, past borrowing relationships and size—were simply impediments that stood in the way of getting a PPP loan. Thus, quite apart from issues of racial bias, a program that effectively favored larger businesses in close proximity to banks or with past borrowing relationships to banks, even if it did so unintentionally, was less successful than it might have been in serving the emergency funding needs of minority-owned businesses.

References

Autor, D., D. Cho, L. D. Crane, M. Goldar, B. Lutz, J. Montes, W. B. Peterman, D. Ratner, D. Villar, and A. Yildirmaz. 2020. An evaluation of the Paycheck Protection Program using administrative payroll microdata. *Working paper* http://economics.mit.edu/files/20094.

Bartik, A., Z. Cullen, E. L. Glaeser, M. Luca, C. Stanton, and A. Sunderam. 2020. The Targeting and Impact of Paycheck Protection Program Loans to Small Businesses. *Working paper* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3676759.

Blanchard, L., B. Zhao, and J. Yinger. 2008. Do lenders discriminate against minority and woman entrepreneurs? *Journal of Urban Economics* 63:467–97. doi:10.1016/j.jue.2007.03.001.

Blanchflower, D. G., P. B. Levine, and D. J. Zimmerman. 2003. Discrimination in the small-business credit market. *Review of Economics and Statistics* 930–43. doi:10.1162/003465303772815835.

Cavalluzzo, K., and J. Wolken. 2005. Small Business Loan Turndowns, Personal Wealth, and Discrimination. *The Journal of Business* 78:2153–78. doi:10.1086/497045.

Erel, I., and J. Liebersohn. 2020. Does Fintech Substitute for Banks? Evidence from the Paycheck Protection Program. *Working paper* http://www.ssrn.com/abstract=3650510.

Fairlie, R. W., A. Robb, and D. T. Robinson. 2020. Black and white: Access to capital among minority-owned startups. *NBER working paper 28154* https://www.nber.org/system/files/working_papers/w28154/w28154.pdf.

Federal Reserve Banks. 2021. Small Business Credit Survey: 2021 report on the firms owned by people of color. https://www.fedsmallbusiness.org/survey/2021/2021-report-on-firms-owned-by-people-of-color.

Fryer, Jr., R. G., and S. D. Levitt. 2008. The causes and consequences of distinctly Black names. *The Quarterly Journal of Economics* 119:767–805. doi:10.1162/0033553041502180.

Ganong, P., D. Jones, P. Noel, D. Farrell, F. Greig, and C. Wheat. 2020. Wealth, Race, and Consumption Smoothing of Typical Income Shocks. *Working paper* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3583707.

Glover, D., A. Pallais, and W. Pariente. 2017. Discrimination as a self-fulfilling prophecy: Evidence from french grocery stores. *Quarterly Journal of Economics* 132:1219–60. doi:10.1093/qje/qjx006.

Granja, J., C. Makridis, C. Yannelis, and E. Zwick. 2020. Did the Paycheck Protection Program hit the target? *Working paper* https://www.nber.org/papers/w27095.pdf.

Griffin, J. M., S. Kruger, and P. Mahajan. 2021. Did FinTech lenders facilitate PPP fraud? *Working paper* .

Hehman, E., J. K. Flake, and J. Calanchini. 2018. Disproportionate use of lethal force in policing is associated with regional racial biases of residents. *Social Psychology and Personality Science* 9:393–401. doi:10.1177/1948550617711229.

Howell, S. T., T. Kuchler, D. Snitkof, J. Stroebel, and J. Wong. 2021. Racial Disparities in Access to Small Business Credit: Evidence from the Paycheck Protection Program. *Working paper* https://www.nber.org/papers/w29364.

Hubbard, R. G., and M. Strain. 2021. Has the Paycheck Protection Program Succeeded? *Working paper* doi:10.3386/w28032.

Li, L., and P. Strahan. 2021. Who supplies PPP loans (and does it matter)? Banks, relationships, and the COVID crisis. *Working paper* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3756318.

Luck, S., and J. A. C. Santos. 2021. The valuation of collateral in bank lending. *Working paper* doi:10.2139/ssrn.3467316.

National Community Reinvestment Coalition. 2020a. Lending discrimination during Covid-19. https://www.ncrc.org/lending-discrimination-during-covid-19-black-and-hispanic-women-owned-businesses/.

———. 2020b. Lending discrimination within the Paycheck Protection Program. https://www.ncrc.org/lending-discrimination-within-the-paycheck-protection-program/.

Wang, J., and D. H. Zhang. 2020. The cost of banking deserts: Racial disparities in access to PPP lenders and their equilibrium implications. *Working paper* https://davidzhang.scholar.harvard.edu/files/dhz/files/geographyppp.pdf.

Appendix

Table A1
Variable Definitions

Variable	Definition
Firm characteristics	
Number of seats	Number of seats reported on the restaurant's license.
Firm age	Years between February 15, 2020 and the first filing date in Florida corporate records.
Bank/nonbank UCC loan	Indicator variable for whether the firm had any active UCC filings as of February 15, 2020 with banks/nonbanks as the secured party. We match debtors in Florida UCC filings to Florida corporate records. We match secured parties to the list of financial institutions maintained by the National Information Center and to Capital IQ. UCC3 filings are used to track continuations, terminations, and changes in debtor and secured parties.
Number of reviews	Number of Yelp reviews as of February 2020.
Average rating	Average Yelp rating as of February 2020. Set to zero for restaurants without any reviews. We separately include an indicator variable for no reviews.
Page views	Average number of monthly Yelp profile views between March 2019 and February 2020.
Number of photos	Average number of photos posted to the restaurant's Yelp profile each month between March 2019 and February 2020.
Accepts credit cards	Indicator variable equal to one if the restaurant accepts credit cards according to its Yelp profile. Set to one for restaurants with missing information. We separately include an indicator variable for missing credit card information. Measured as of March 11, 2020.
Employees	Number of employees as of 2019 from Dun & Bradstreet.
Sales	2019 sales from Dun & Bradstreet. Sales are almost always modelled by Dun & Bradstreet.
County characteristics	
Explicit racial bias	Response to the question "Which statement best describes you? 1 'I strongly prefer African American to European Americans', 2 'I moderately prefer African Americans to European Americans' ... 4 'I like European Americans and African Americans equally' ... 7 'I strongly prefer European Americans to African Americans."' (variable name `att7`) We calculate county-level average across all white respondents taking the test between 2008 and 2019. County-level racial bias is standardized to have zero mean and standard deviation equal to one.
Implicit racial bias	Overall score on the Race Implicit Association Test (variable name `D_biep.White_Good_all`). We calculate county-level average across all white respondents taking the test between 2008 and 2019. County-level racial bias is standardized to have zero mean and standard deviation equal to one.
ZIP code characteristics	
Bank branches per capita	Number of bank branches in the ZIP code divided by population. Number of bank branches in the ZIP code is from the June 2019 Summary of Deposits. Estimate of the 2019 ZIP Code Tabulation Area (ZCTA) population (variable name `B02001_001E`) is from the 2019 American Community Survey.
White population share	Estimate of white alone population (variable name `B02001_002E`) divided by estimate of total population (variable name `B02001_001E`) from the 2019 American Community Survey.

Table A1
Table A1—*Continued*

Variable	Definition
Median household income	Median household income in the past 12 months (variable name `S1901_C01_012E`) from the 2019 American Community Survey.
Population	Estimate of total population (variable name `B02001_001E`) from the 2019 American Community Survey.

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. Three-quarters of all restaurants are matched in this step.

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.

Linking restaurant owners to voter registration

We combine two snapshots of Florida voter registration data: January 31, 2017 and January 31, 2021.[24] The most recent snapshot accounts for 89% of all voter records. The older snapshot includes voters who may have been deregistered for various reasons.

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.[25]
   (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.

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

[25] 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.

(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.

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	583	21.6
KABBAGE	419	15.5
WEBBANK	372	13.8
CELTIC BANK CORP	329	12.2
READYCAP LENDING LLC	219	8.1
ITRIA VENTURES LLC	204	7.5
SQUARE CAPITAL LLC	68	2.5
FOUNTAINHEAD SBF LLC	67	2.5
HARVEST SMALL BUSINESS FINANCE LLC	49	1.8
NEWTEK SMALL BUSINESS FINANCE	44	1.6
INTUIT FINANCING	39	1.4
BSD CAPITAL LLC	33	1.2
BENWORTH CAPITAL	29	1.1
FC MARKETPLACE LLC	28	1.0
MBE CAPITAL PARTNERS	22	0.8
CENTERSTONE SBA LENDING	19	0.7
CAPITAL PLUS FINANCIAL LLC	19	0.7
DREAMSPRING	18	0.7
LIBERTY SBF HOLDINGS LLC	16	0.6
FUNDBOX	16	0.6
AMUR EQUIPMENT FINANCE	12	0.4
PRESTAMOS CDFI LLC	11	0.4
AMERICAN LENDING CENTER	11	0.4
A10CAPITAL LLC	10	0.4
ENTERPRISE CENTER CAPITAL CORP	10	0.4
BLACK BUSINESS INVESTMENT FUND	9	0.3
SUNSHINE STATE ECONOMIC DEVELOPMENT CORP	9	0.3
ASCENDUS	7	0.3
TIMEPAYMENT CORP	6	0.2
CRF SMALL BUSINESS LOAN COMPANY LLC	6	0.2
FIRST EQUITY MORTGAGE BANKERS	3	0.1
LIFTFUND	2	0.1
FUND-EX SOLUTIONS GROUP LLC	2	0.1
CDC SMALL BUSINESS FINANCE CORP	2	0.1
HOPE ENTERPRISE CORP	2	0.1
INDEPENDENT DEVELOPMENT SERVICES CORP	2	0.1
OPPORTUNITY FUND COMMUNITY DEVELOPMENT	2	0.1
FARM CREDIT OF CENTRAL FLORIDA ACA	1	0.0
WORLD TRADE FINANCE	1	0.0
IMMITO LLC	1	0.0

Table A3
Robustness to Controlling for County Characteristics

This table shows the robustness of the results in Table 7 to controlling for the interaction between *Black* and county characteristics. 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%. Continuous variables are standardized so that their coefficients represent the effect of a one standard deviation change. $N = 9,980$.

	PPP		Bank PPP		Nonbank PPP		EIDL	
	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit	Explicit	Implicit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	−0.179***	−0.159***	−0.257***	−0.177***	0.078	0.018	0.056*	0.106***
	(0.062)	(0.056)	(0.033)	(0.024)	(0.048)	(0.049)	(0.029)	(0.030)
Hispanic	−0.031	−0.031	−0.021	−0.021	−0.011	−0.011	0.062***	0.062***
	(0.022)	(0.022)	(0.028)	(0.028)	(0.006)	(0.006)	(0.017)	(0.017)
Asian	0.002	0.002	−0.058***	−0.057***	0.059***	0.059***	0.005	0.005
	(0.014)	(0.014)	(0.021)	(0.021)	(0.016)	(0.016)	(0.036)	(0.036)
Other	−0.007	−0.007	−0.041	−0.041	0.034	0.034	0.054**	0.054**
	(0.035)	(0.035)	(0.031)	(0.031)	(0.022)	(0.022)	(0.022)	(0.022)
Female	−0.010	−0.010	−0.026***	−0.026***	0.017*	0.017*	−0.003	−0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.012)	(0.012)
Black × Bias	−0.021	−0.108	−0.174***	−0.383***	0.153*	0.275*	−0.127**	−0.230***
	(0.122)	(0.225)	(0.057)	(0.101)	(0.083)	(0.154)	(0.054)	(0.084)
Black × Personal income	−0.051	−0.028	−0.020	0.046	−0.031	−0.074**	0.062***	0.098***
	(0.031)	(0.058)	(0.021)	(0.030)	(0.021)	(0.032)	(0.020)	(0.023)
Black × Unemployment rate	0.122**	0.143**	0.097**	0.148***	0.025	−0.004	0.165***	0.189***
	(0.056)	(0.069)	(0.039)	(0.040)	(0.040)	(0.052)	(0.044)	(0.047)
Black × White population share	0.091*	0.087*	0.011	−0.001	0.080**	0.088***	−0.085*	−0.091**
	(0.051)	(0.046)	(0.036)	(0.031)	(0.031)	(0.028)	(0.046)	(0.045)
Black × Ln(Population)	0.238**	0.235**	0.093*	0.108**	0.145*	0.128	−0.101**	−0.087**
	(0.105)	(0.102)	(0.051)	(0.047)	(0.084)	(0.081)	(0.047)	(0.043)
Log(Number of seats)	0.040***	0.040***	0.044***	0.045***	−0.005	−0.005	0.003	0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.006)	(0.006)
Ln(Firm age)	0.034***	0.034***	0.041***	0.041***	−0.007*	−0.007*	−0.015*	−0.015*
	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.008)	(0.008)
Accepts credit cards	0.166***	0.166***	0.136***	0.135***	0.030***	0.031***	0.088*	0.087*
	(0.033)	(0.033)	(0.035)	(0.035)	(0.010)	(0.010)	(0.048)	(0.048)
Missing credit cards	−0.020	−0.020	−0.005	−0.005	−0.015	−0.015	−0.005	−0.005
	(0.033)	(0.033)	(0.025)	(0.025)	(0.014)	(0.014)	(0.012)	(0.012)
Ln(Reviews)	0.036***	0.036***	0.035***	0.035***	0.001	0.001	0.018	0.018
	(0.007)	(0.007)	(0.010)	(0.010)	(0.004)	(0.004)	(0.013)	(0.013)
Average rating	0.000	0.000	0.002	0.002	−0.001	−0.002	0.043**	0.043**
	(0.017)	(0.017)	(0.014)	(0.014)	(0.006)	(0.006)	(0.019)	(0.019)
No reviews	−0.071	−0.071	−0.057	−0.057	−0.014	−0.014	0.096**	0.096**
	(0.078)	(0.078)	(0.065)	(0.065)	(0.031)	(0.032)	(0.047)	(0.047)
Ln(Page views)	0.005	0.005	0.004	0.004	0.000	0.001	−0.005	−0.005
	(0.011)	(0.011)	(0.009)	(0.009)	(0.010)	(0.010)	(0.014)	(0.014)
Ln(Photos)	0.039***	0.039***	0.049***	0.049***	−0.010	−0.010	−0.009	−0.009
	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.012)	(0.012)
Bank UCC loan	0.040***	0.040***	0.063***	0.063***	−0.024***	−0.024***	0.053***	0.053***
	(0.015)	(0.015)	(0.019)	(0.019)	(0.006)	(0.006)	(0.011)	(0.011)
Nonbank UCC loan	0.048***	0.048***	0.013	0.013	0.035***	0.035***	0.106***	0.106***
	(0.016)	(0.016)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)
R^2	0.170	0.170	0.180	0.180	0.103	0.103	0.098	0.098
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table A4
Gender-Career Bias

This table reports the results of linear probability model regressions of receiving different types of emergency loans on the interaction between female owner and county-level gender-career bias:

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

where c indexes counties, f indexes firms, r indexes restaurants, and z indexes ZIP codes. Gender-career bias is based on the responses to the Gender-Carreer Implicit Association Test, which measures the implicit association between family and females and between career and males. County-level averages of gender-career bias are standardized so that the interaction terms represent the effect of a one standard deviation increase in bias. Regressions are weighted by the number of respondents to the test during the 2005–2019 period. Controls include all restaurant characteristics included in the regression in column 2 of Table 6. Standard errors are adjusted for clustering by county. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Continuous variables are standardized so that their coefficients represent the effect of a one standard deviation change. $N = 9,980$.

	PPP		Bank PPP		Nonbank PPP		EIDL	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	-0.205^{***}	-0.121^{**}	-0.263^{***}	-0.170^{***}	0.058	0.049	0.017	0.026
	(0.044)	(0.054)	(0.024)	(0.022)	(0.048)	(0.050)	(0.038)	(0.040)
Hispanic	-0.064^{**}	-0.027	-0.058^{*}	-0.018	-0.005	-0.009	0.068^{***}	0.071^{***}
	(0.027)	(0.024)	(0.032)	(0.029)	(0.006)	(0.006)	(0.012)	(0.012)
Asian	-0.019	0.003	-0.077^{***}	-0.052^{**}	0.058^{***}	0.055^{***}	0.003	0.012
	(0.012)	(0.012)	(0.018)	(0.023)	(0.017)	(0.018)	(0.037)	(0.038)
Other	-0.020	0.001	-0.060^{*}	-0.037	0.041	0.038	0.062^{***}	0.068^{***}
	(0.040)	(0.041)	(0.034)	(0.037)	(0.025)	(0.025)	(0.017)	(0.018)
Female	-0.028^{***}	-0.012	-0.054^{***}	-0.036^{***}	0.026^{**}	0.024^{**}	-0.006	-0.004
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.011)	(0.012)
Female × Bias	-0.040	-0.020	-0.131^{**}	-0.111^{***}	0.091^{**}	0.090^{**}	-0.045	-0.032
	(0.031)	(0.027)	(0.051)	(0.037)	(0.045)	(0.044)	(0.075)	(0.077)
R^2	0.112	0.171	0.118	0.179	0.090	0.095	0.086	0.098
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓		✓

Table A5
UCC Lending Relationships

This table reports the full output of the regressions in Table 6.

	PPP			Bank PPP			Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Black	-0.098^{***}	-0.099^{***}	-0.070^{**}	-0.166^{***}	-0.164^{***}	-0.145^{***}	0.067^{***}	0.065^{***}	0.075^{***}	0.054^{*}	0.050^{*}	0.050
	(0.028)	(0.028)	(0.031)	(0.027)	(0.027)	(0.029)	(0.019)	(0.019)	(0.021)	(0.029)	(0.029)	(0.031)
Hispanic	-0.032^{**}	-0.030^{**}	-0.029^{*}	-0.035^{**}	-0.032^{**}	-0.032^{*}	0.003	0.002	0.003	0.042^{***}	0.043^{***}	0.040^{**}
	(0.015)	(0.015)	(0.017)	(0.015)	(0.015)	(0.017)	(0.008)	(0.008)	(0.008)	(0.016)	(0.016)	(0.017)
Asian	0.007	0.014	0.013	-0.067^{***}	-0.059^{***}	-0.063^{***}	0.074^{***}	0.074^{***}	0.076^{***}	0.014	0.023	0.013
	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.019)	(0.011)	(0.011)	(0.012)	(0.018)	(0.018)	(0.019)
Other	-0.011	-0.007	0.011	-0.043^{*}	-0.040	-0.025	0.032^{**}	0.033^{**}	0.036^{**}	0.047^{*}	0.052^{*}	0.054^{*}
	(0.025)	(0.025)	(0.028)	(0.026)	(0.026)	(0.029)	(0.015)	(0.015)	(0.017)	(0.027)	(0.027)	(0.030)
Female	-0.007	-0.005	-0.008	-0.017	-0.015	-0.012	0.010^{*}	0.010	0.005	-0.005	-0.002	0.004
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.006)	(0.006)	(0.007)	(0.011)	(0.011)	(0.013)
Log(Number of seats)	0.049^{***}	0.045^{***}	0.058^{***}	0.055^{***}	0.050^{***}	0.062^{***}	-0.006^{*}	-0.006^{*}	-0.004	0.012^{**}	0.006	0.009
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)	(0.006)
Ln(Firm age)	0.036^{***}	0.033^{***}	0.037^{***}	0.043^{***}	0.040^{***}	0.043^{***}	-0.008^{***}	-0.007^{***}	-0.006^{*}	-0.014^{**}	-0.018^{***}	-0.013^{**}
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)
Accepts credit cards	0.188^{***}	0.178^{***}	0.175^{***}	0.161^{***}	0.150^{***}	0.149^{***}	0.028	0.027	0.026	0.088^{**}	0.073^{*}	0.074^{*}
	(0.041)	(0.041)	(0.040)	(0.041)	(0.040)	(0.040)	(0.017)	(0.017)	(0.017)	(0.038)	(0.039)	(0.039)
Missing credit cards	-0.012	-0.015	-0.014	-0.007	-0.010	-0.009	-0.005	-0.004	-0.005	-0.007	-0.011	-0.011
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.011)	(0.011)	(0.011)	(0.022)	(0.022)	(0.022)
Ln(Reviews)	0.046^{***}	0.044^{***}	0.044^{***}	0.046^{***}	0.044^{***}	0.044^{***}	-0.000	0.000	-0.000	0.013	0.010	0.010
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)	(0.005)	(0.011)	(0.011)	(0.011)
Average rating	-0.020^{**}	-0.017^{*}	-0.019^{**}	-0.014	-0.011	-0.013	-0.006	-0.006	-0.006	0.030^{***}	0.034^{***}	0.034^{***}
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)	(0.005)	(0.010)	(0.010)	(0.010)
No reviews	-0.154^{***}	-0.144^{***}	-0.147^{***}	-0.119^{***}	-0.110^{**}	-0.113^{**}	-0.035	-0.034	-0.035	0.103^{**}	0.118^{***}	0.117^{***}
	(0.044)	(0.044)	(0.044)	(0.045)	(0.044)	(0.044)	(0.024)	(0.024)	(0.024)	(0.045)	(0.046)	(0.045)
Ln(Page views)	0.001	0.001	0.001	-0.007	-0.006	-0.006	0.008	0.007	0.007	0.003	0.003	0.003
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)	(0.012)
Ln(Photos)	0.040^{***}	0.037^{***}	0.038^{***}	0.052^{***}	0.049^{***}	0.050^{***}	-0.012^{***}	-0.012^{***}	-0.012^{***}	-0.005	-0.008	-0.008
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.008)
Bank UCC loan		0.053^{***}	0.080^{***}		0.077^{***}	0.114^{***}		-0.024^{***}	-0.033^{***}		0.054^{***}	0.045^{**}

(Continued)

Table A5—*continued*

	PPP			Bank PPP			Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		(0.012)	(0.016)		(0.013)	(0.017)		(0.006)	(0.008)		(0.014)	(0.020)
Nonbank UCC loan		0.054***	0.076***		0.024*	0.033*		0.030***	0.043***		0.108***	0.143***
		(0.012)	(0.017)		(0.014)	(0.019)		(0.008)	(0.012)		(0.015)	(0.022)
Black × Bank UCC loan			−0.181*			−0.251**			0.070			0.165
			(0.099)			(0.098)			(0.076)			(0.123)
Hispanic × Bank UCC loan			0.025			0.001			0.024			0.078*
			(0.033)			(0.035)			(0.018)			(0.042)
Asian × Bank UCC loan			0.054			−0.009			0.063			0.179***
			(0.042)			(0.054)			(0.042)			(0.060)
Other × Bank UCC loan			−0.067			−0.020			−0.047**			−0.046
			(0.069)			(0.069)			(0.022)			(0.075)
Female × Bank UCC loan			0.033			0.018			0.015			0.018
			(0.028)			(0.030)			(0.016)			(0.035)
Ln(Seats)× Bank UCC loan			−0.073***			−0.075***			0.002			−0.017
			(0.013)			(0.013)			(0.006)			(0.015)
Ln(Firm age)× Bank UCC loan			−0.020			−0.018			−0.002			−0.038**
			(0.013)			(0.013)			(0.006)			(0.016)
Black × Nonbank UCC loan			−0.096			0.017			−0.112**			−0.083
			(0.076)			(0.079)			(0.046)			(0.083)
Hispanic × Nonbank UCC loan			−0.013			0.018			−0.030			−0.063
			(0.033)			(0.037)			(0.022)			(0.040)
Asian × Nonbank UCC loan			−0.012			0.071			−0.083**			−0.059
			(0.047)			(0.055)			(0.037)			(0.061)
Other × Nonbank UCC loan			−0.053			−0.074			0.021			0.025
			(0.075)			(0.079)			(0.056)			(0.084)
Female × Nonbank UCC loan			−0.012			−0.044			0.032			−0.059
			(0.029)			(0.033)			(0.021)			(0.036)
Ln(Seats)× Nonbank UCC loan			−0.023*			−0.007			−0.016*			−0.005
			(0.013)			(0.014)			(0.008)			(0.016)
Ln(Firm age)× Nonbank UCC loan			−0.030**			−0.017			−0.013			−0.010

(Continued)

Table A5—*continued*

	PPP			Bank PPP			Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			(0.015)			(0.017)			(0.010)			(0.019)
Constant	0.614***	0.596***	0.605***	0.565***	0.549***	0.555***	0.049*	0.048*	0.050*	0.145***	0.119**	0.122**
	(0.054)	(0.054)	(0.054)	(0.055)	(0.055)	(0.055)	(0.027)	(0.027)	(0.027)	(0.054)	(0.054)	(0.054)
R^2	0.179	0.183	0.188	0.191	0.195	0.199	0.109	0.112	0.115	0.100	0.107	0.110
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓