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RACIAL DISPARITIES IN THE PAYCHECK PROTECTION PROGRAM

Sergey Chernenko
David S. Scharfstein

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ABSTRACT

Using a large sample of Florida restaurants, we document significant racial disparities in borrowing through 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 explain an additional 10 percentage points of the gap in PPP borrowing. On average, prior borrowing relationships do not explain disparities. The remaining 10% disparity is driven by a 17% disparity in PPP borrowing from banks, which is partially offset by greater borrowing from nonbanks, largely fintechs. Disparities in PPP borrowing cannot be attributed to lower awareness of PPP loans or lower demand for PPP loans by minority-owned restaurants. Black-owned restaurants are significantly less likely to receive bank PPP loans in counties with more racial bias. In these counties, Black-owned restaurants are more likely to substitute to nonbank PPP loans. This substitution, however, is not strong enough to eliminate racial disparities in PPP borrowing. Finally, we show that our findings apply more broadly across industries in a sample of firms that were likely eligible for PPP.

Sergey Chernenko
Krannert School of Management
Purdue University
403 W. State Street
West Lafayette, IN 47907
schernen@purdue.edu

David S. Scharfstein
Harvard Business School
Baker Library 363
Soldiers Field
Boston, MA 02163
and NBER
dscharfstein@hbs.edu

A Internet Appendix is available at
https://drive.google.com/file/d/1-2dioQkxuQJ4sgpIJLJBYq7NPXuga5e9/view?usp=sharing

1 Introduction

The Paycheck Protection Protection (PPP), authorized by the CARES Act in March 2020, was a key component of the U.S. government's response to the adverse economic effects of the COVID-19 pandemic. Under PPP, the Small Business Administration (SBA) guaranteed about $800 billion in low-interest 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 firms most needing support, whether it was subject to considerable amounts of fraud, and whether it provided equal access to minority-owned firms.

This paper provides the first systematic micro-level analysis of the uptake of PPP by minority-owned businesses. We document significant disparities in PPP borrowing 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 determine the identity of the restaurant owner. Voter registration data tell us the restaurant owner's self-identified racial and Hispanic identity. Data on firms' existing secured loans enable us to examine the effect of prior borrowing relationships on PPP uptake. Detailed data on restaurant characteristics from state licenses and Yelp allow us to control for differences among restaurants that could affect PPP loan supply and demand.

To help us understand racial disparities in PPP, we also contrast PPP with the Economic Injury Disaster Loan (EIDL) program, an existing SBA program that was significantly expanded to mitigate the adverse economic impact of the pandemic. As part of this program, the SBA made non-forgivable low-interest loans directly to small businesses without using financial intermediaries. It also made grants up to $10,000 under the EIDL Advance program. Studying EIDL in combination with PPP allows us to control for differences in firm and owner characteristics that might affect the demand for emergency support. It also helps us expand our analysis to other industries by identifying firms that were likely eligible for PPP loans.

We start by documenting that Black-owned restaurants are 25.0% less likely than 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.

The disparities in overall PPP borrowing are driven by disparities in bank borrowing. 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%. Except for Hispanic-owned restaurants, these disparities in bank borrowing tend to be offset by greater borrowing from nonbank PPP lenders—largely fintechs. While the substitution is large enough to eliminate disparities in PPP borrowing for Asian-owned restaurants, this is not the case for Black-, Hispanic- and female-owned restaurants, which are still less likely than white-owned restaurants to receive PPP funding. Moreover, the racial disparities we document in PPP do not exist in the EIDL program; if anything, minority-owned restaurants, particularly Hispanic-owned ones, are more likely to receive EIDL loans. As noted, these loans are not intermediated by banks but rather are made directly by the SBA.

What explains these disparities in PPP uptake, particularly the much lower rate of PPP borrowing by Black-owned restaurants? We consider four potential explanations: 1) location; 2) firm characteristics; 3) pre-existing borrowing relationships; and 4) racial bias. The first three—location, characteristics, and borrowing relationships—could explain disparities in PPP borrowing through their effect on PPP loan supply and demand, independent of racial and Hispanic identity. For example, banks may have prioritized PPP loan applications of larger firms and existing clients at the expense of smaller firms without existing borrowing relationships, with the latter firms more likely to be minority-owned. We find that while these factors do explain a portion of the disparities in PPP borrowing, racial bias also plays a significant role.

The first explanation, location, accounts for about 20–30% of the disparity in PPP borrowing by minority-owned businesses. Once we include ZIP code fixed effects in our regressions, estimated disparities in PPP borrowing fall from 25.0% to 19.8% for Black-owned businesses and from 9.1% to 6.3% for Hispanic-owned businesses. About three-quarters of the ZIP code fixed effect can be explained by 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 and the number of reviews and photos. Older, larger, and more heavily visited and reviewed restaurants are more likely to receive PPP funding. Controlling for these characteristics reduces the disparity for Black-owned restaurants by another 10 percentage points, or 40% of the unconditional disparity. However, Black-owned restaurants are still 9.8% less likely to receive PPP loans. For Hispanic-owned restaurants, the disparity in PPP borrowing is cut by a similar percentage with the inclusion of these firm characteristics, resulting in a 3.2% disparity in PPP borrowing.

A third explanation for disparities in PPP uptake is that minority-owned firms may have had weaker relationships with banks. This could explain the findings if banks prioritized their existing clients at a time when banks had limited capacity to process applications. While we cannot measure an entire banking relationship, including different types of loans, checking accounts, credit cards, and merchant services, we use data on Uniform Commercial Code (UCC) filings to determine whether a firm had outstanding secured loans. 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 use business checking accounts and merchant services.

We find that while minority-owned restaurants are much less likely to have outstanding secured bank loans, controlling for their prior bank borrowing does little to reduce the measured disparities in bank PPP borrowing. There are still substantial disparities in the large subsample of firms—over 80% of the full sample—that do not have bank borrowing relationships. The disparities are even larger between Black- and white-owned restaurants that have bank borrowing relationships; while white-owned restaurants with a bank borrowing relationship are more likely to access PPP loans, this is not the case for Black-owned restaurants. This finding suggests that banks either do not prioritize Black-owned businesses with which they have borrowing relationships or Black business owners are more dissatisfied with their bank lenders and thus less likely to apply for a PPP loan from a bank.

The final explanation is that disparities in PPP borrowing are affected by racial bias. It is possible that there was racial bias in the way banks processed PPP loan applications. Indeed, audit studies by the National Community Reinvestment Coalition (NCRC) find 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). It is also possible that even if there was no discrimination in the application process at banks, a legacy of past discrimination and poor treatment discouraged minority-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. Yet it is possible that despite the inclusion of these controls, there are still unobserved factors that could explain the estimated disparities. These unobserved factors, however, would also have to explain why minority-owned restaurants are less likely to get bank PPP loans but are more likely to get nonbank PPP loans and EIDL loans than otherwise comparable white-owned restaurants. Nevertheless, to alleviate concerns about unobserved factors and provide more direct evidence of the role of racial bias, we examine whether racial disparities in bank PPP borrowing are greater in counties with more racial bias. 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.[1]

Our findings indicate that Black-owned restaurants in counties where 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 13.9 percentage-point reduction in the probability that a Black-owned restaurant receives a PPP loan from a bank. Moreover, in more racially biased counties, Black-owned businesses are much more likely to substitute to nonbank PPP loans and EIDL loans from the SBA, though latter effect is imprecisely estimated. Because applications to nonbanks and the SBA are typically made online, while applications to banks often involve more personal interaction, there may have been less scope for racial bias in the application process at nonbanks and the SBA. This may help explain why Black business owners are more likely to use these funding sources.

We also examine whether 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 the disparity for Black-owned restaurants, although disparities remain. We also find that racial disparities in the third round were not greater in more racially biased counties.

We next explore whether the estimated disparities in PPP uptake could be explained by lower demand for PPP loans by minority-owned restaurants even though we have included extensive controls for demand. On its face, this explanation of disparities is unlikely to have much traction given that minority-owned restaurants substituted from bank PPP loans to

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

nonbank PPP loans and EIDL loans. Nevertheless, minority-owned restaurants may have been more vulnerable to the pandemic and were thus more likely to shut down and not apply for PPP loans. However, we do not find that this is the case; controlling for observable characteristics, minority-owned restaurants are no more likely to shut down than white-owned restaurants. Moreover, our findings on a restricted sample of surviving restaurants are similar to our findings in the full sample. Controlling for restaurant visits during the pandemic also does not affect the estimated racial disparities in PPP borrowing.

We also address the concern that racial disparities are driven by lower demand for PPP loans from minority-owned restaurants by examining PPP uptake in a sample of firms that received grants of $1,000 per employee, up to a total of 10 employees, as part of the EIDL Advance program. Focusing on these grant recipients allows us to analyze PPP borrowing in a sample of firms with demonstrated awareness of government emergency support programs and demand for such support. It also allows us to directly control for the number of employees. We find that among firms that receive EIDL Advance grants, Black-owned businesses are significantly less likely to receive PPP loans than white-owned businesses with the same number of employees. Moreover, in this sample, the disparity in bank PPP borrowing is greater in more racially biased counties.

Finally, we examine 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 PPP uptake, we can study disparities in PPP borrowing among the sample of firms that receive EIDL Advance grants. In regressions with ZIP code cross industry fixed effects and controls for firm age, sales, employees, and secured borrowing relationships, Black- and Hispanic-owned businesses are significantly less likely to receive PPP loans. In addition, Black-owned businesses are less likely to receive PPP loans from banks in more racially biased counties. We find similar results in a sample of firms that receive either a PPP loan or an EIDL loan; in this sample, minority-owned businesses are less likely to receive PPP loans, and they are less likely to receive them from banks.

Our paper is part of a growing literature studying the functioning and impact of PPP,[2] 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 less PPP uptake, measured by the ratio of PPP loans to the number of establishments in a ZIP code. They

[2] 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).

find that less PPP uptake 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. Indeed, we show that ZIP code fixed effects account for only one-fifth of racial disparities in PPP borrowing, while firm characteristics and racial bias have a much larger impact.

In a contemporaneous paper analyzing the full population of PPP borrowers, 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 a similar vein, Fei and Yang (2021) use the sample of PPP borrowers matched to Yelp-listed restaurants to show that minority-owned restaurants are more likely to get their PPP loans from fintech lenders rather than from banks. Both Howell et al. (2021) and our paper find that Black-owned businesses are more likely to borrow from fintechs in more racially biased locations and that controlling for prior banking relationships does not meaningfully reduce average disparities in bank PPP funding. All three papers suggest that online loan application processes attenuate racial disparities in PPP uptake. However, there are at least two distinctive features of our paper. First and most importantly, because we focus on restaurants, we can 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) and Fei and Yang (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, this substitution is not enough to offset the disparity in bank PPP funding. Thus, we can conclude that racial bias has real effects on PPP uptake. Second, by linking business owners to voter registration data, we have a more accurate measure of race and Hispanic identity than either the machine learning algorithm used in Howell et al. (2021) or the approach based on restaurant cuisine used in Fei and Yang (2021). As argued below, such measurement error can inflate or deflate the estimated effects.

In addition to contributing to the growing literature on PPP, our paper contributes to a broader literature on discrimination in small business lending. Blanchflower, Levine, and Zimmerman (2003), Cavalluzzo and Wolken (2005), Blanchard, Zhao, and Yinger (2008), and 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 less likely 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 racial bias, consistent with our findings. These studies suggest that our findings could, in part, be driven by a historical legacy of discrimination that discouraged 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 documents the existence of racial disparities in PPP borrowing, showing that they are driven by disparities in PPP borrowing from banks and that there is only a partial substitution to nonbank sources of PPP funding. We also document the role of location and restaurant characteristics in explaining racial disparities in PPP borrowing. We examine whether differences in bank relationships could explain racial disparities in Section 4, and we then examine the role of racial bias in Section 5. Section 6 provides evidence against the view that racial disparities in PPP borrowing can be explained by lower demand from minority-owned businesses for emergency loans. Section 7 explores the external validity of our findings by examining a broader sample of Florida businesses that receive emergency support. Section 8 concludes.

2 Data

Our main data set is composed of restaurants in Florida with information on the owner's racial and Hispanic identity. We construct the main sample by combining information from the following data sets: 1) Florida restaurant licenses; 2) Florida corporate records; 3) Florida voter registration; and 4) Yelp data on restaurant characteristics and activity. We then determine whether each restaurant in the sample 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. Details on the sample construction and the data are described below.

2.1 PPP and EIDL Loans

Data on approved PPP and EIDL loans are from the SBA website.[3] PPP loan data include all loans approved during the periods April 3–August 9, 2020 and January 11–June 30, 2021. EIDL data include loans approved through November 14, 2020. The SBA has not yet released loan-level data on the EIDL loans made after this date. In 2020, the SBA made 3.6 million EIDL 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. However, most of our analyses compare PPP and EIDL loans extended during 2020. Both PPP and EIDL data report the borrower's name and location, loan amount, and approval date. PPP loan data also report the lender's name and location, the borrower's industry, and self-reported demographic information on the borrower. The vast majority of PPP borrowers (83%) do not report information on their racial and 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 Internet 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 eligible borrowers. We overcome this limitation by studying the uptake of PPP and EIDL loans by Florida restaurants.[4] 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.[5]

To generate a relatively homogeneous sample, we focus on restaurants that offer seating, while excluding food trucks, takeout-only restaurants, and caterers. We also exclude

[3] 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

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

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

restaurants with licenses approved after February 15, 2020 because they would not have been eligible for PPP. Finally, we exclude hotel restaurants and franchise restaurants because they are frequently owned and operated by affiliated entities. As a result, it can be difficult to determine whether a given hotel or franchise restaurant received an emergency loan or benefited from a parent receiving an emergency loan.[6] Restaurants are classified as being in a hotel if they share the same address as one of the hotels in Florida hotel license data.[7] We classify restaurants as franchises based on restaurant names.

Restaurant license data identify the name and location of the restaurant as well as the license holder. We match license holders to Florida corporate records. Most license holders are firms, enabling a straightforward match based on 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 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 can match 91% of restaurants that meet the sample selection criteria. 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,[8] and publicly-traded firms. We also exclude restaurants matched to firms registered for the first time after February 15, 2020.

2.3 Racial and Hispanic Identity of Potential Borrowers

We classify firms based on the racial and 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.

[6] In the robustness analyses in Table IA1, we use an algorithm to identify affiliated firms and find larger disparities in bank PPP borrowing when we measure borrowing across all of the restaurant's affiliates.

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

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

Table 1
Florida Restaurants Sample

This table summarizes the sample selection criteria and the number of restaurants at each step in the construction of the sample. Details of the matching algorithm used in the sample construction are described in the Internet 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	1,113	9,980

Regression results that use predicted racial and 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 and Hispanic identity, with the magnitude of the bias depending on the relative accuracy with which the algorithm classifies different groups.

In addition to introducing biases in the estimates of the direct effect of racial and Hispanic identity, name-based algorithms could introduce biases in the indirect effects of racial and Hispanic identity to the extent that the measurement error is correlated with firm and location characteristics. Fryer and Levitt (2008) show that the use of distinctly Black names varies over time and is strongly correlated with socioeconomic status. Thus, for example, if there is less measurement error in more racially biased locations, it is possible that the estimated disparities in PPP uptake in more racially biased locations are overstated because the racial bias measure is really capturing the extent of measurement error in the name-based algorithm. Similarly, if Black-owned businesses are less likely to have existing bank relationships, then measures of bank relationships may provide incremental information relative to a name-based algorithm about whether the business owner is Black.

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 and Hispanic identity.[9] Voter registrants can identify themselves 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.[10] Because of the small number of

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

[10] Ganong et al. (2020) show that there is a 99% agreement rate between the way voters identify themselves

observations, we include voters self-identified as American Indian or Alaska Native or multi-racial in the "other" category. For brevity, we refer to "Asian or Pacific Islander" as Asian, "Black, not Hispanic" as Black, and "white, not Hispanic" as white. These classifications are imperfect, in part because they do not separate race from ethnic identity. Notably, unlike the Census, Florida voter registration only offers "Black" and "Hispanic" as mutually exclusive categories.

We match the firm's owner to voter registration data based on name and location. Details of the matching algorithm are provided in the Internet Appendix. For 56% of the sample restaurants, we are able to identify a restaurant owner's racial and Hispanic identity. 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 and 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 being a registered voter, we exclude restaurants that may have been ineligible for PPP funding.[11] 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 thus may be more likely to apply for a PPP loan.

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. We use features

in a matched sample of voter registration files and mortgage applications.

[11] 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.

that were in place just before the pandemic. We also have user activity measures, including the number of reviews and photos posted each week, the average rating, and the number of page visits. 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.

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, firms that use more advanced financial technology to process loan applications online.

2.6 Bank Relationships

We measure borrowing relationships using Uniform Commercial Code (UCC) filings.[12] Lenders file UCC financing statements to establish priority in the collateral pledged to them. Using Florida UCC filings data,[13] we match debtors to Florida corporate records. We match lenders to the National Information Center (NIC) and Capital IQ, and we 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 from a bank or a nonbank.

[12] Gopal (2021) and Gopal and Schnabl (2020) also use UCC filings to measure lending to small businesses. These papers provide more details on UCC filings.

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

2.7 Summary Statistics

Table 2 reports summary statistics for the main 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 materially affect the types of firms we are studying.

Table 2
Summary Statistics

This table reports summary statistics for the main sample of Florida restaurants and for the larger sample of restaurants not matched to voter registration and Yelp data. The main sample is composed of restaurants with seating that, as of February 15, 2020: 1) were licensed in Florida; 2) were registered as Florida for-profit firms; 3) had an owner whose racial and Hispanic identity can be determined from Florida voter registration data; and 4) can be matched to Yelp. Hotel and franchise restaurants are excluded. The corporate records sample is composed of restaurants that meet the above criteria but are not matched to voter registration data and Yelp data.

	Main sample ($N = 9,980$)				Corporate records ($N = 21,762$)			
	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

3 Documenting Disparities

Table 3 reports sample means for restaurant characteristics, location characteristics, and emergency loan uptake for restaurants broken out by the owner's racial and Hispanic identity and by gender. Minority-owned and female-owned restaurants 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. The average rating of Black-owned restaurants is similar to that 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 shares. Black-owned restaurants, for example, are located in ZIP codes in which white people comprise 56% of the overall population. In contrast, white-owned restaurants are located in ZIP codes in which white people comprise 81% of the overall population. Black-owned restaurants are also located in ZIP codes with about 44% fewer bank branches per capita, 19% lower median household income, and 17% higher COVID cases per capita. Our regression 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 the use of emergency loans. Out of white-owned restaurants, 74% receive a PPP loan. Almost all of these are from a bank. A third of white-owned restaurants receive an EIDL loan, with most recipients also receiving a PPP loan. Only 5% of white-owned restaurants receive an EIDL loan without also receiving a PPP loan.

The picture is very different for Black-owned restaurants. Only 48% receive a PPP loan. Conditional on receiving a PPP loan, 29% of PPP loans are from a nonbank. Compared to white-owned restaurants, Black-owned restaurants are three times more likely to receive only an EIDL loan, and 36% of Black-owned restaurants receive neither type of loan. The pattern of outcomes for other minority-owned restaurants is generally in between those for white- and Black-owned restaurants.

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 firm f. A given firm can own multiple restaurants. Table IA1 in the Internet Appendix shows the robustness of our results to analyzing single-restaurant firms, which comprise almost 93% of our sample.

In columns 1–4 of Panel A in Table 4 the dependent variable is equal to one if the restaurant receives 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

Table 3
Uptake of Emergency Loans by Different Groups

This table reports sample means broken out by owner's racial and Hispanic identity, and by gender. Population and median household income are in thousands. The main sample is composed of restaurants with seating that, as of February 15, 2020: 1) were licensed in Florida; 2) were registered as Florida for-profit firms; 3) had an owner whose racial and Hispanic identity can be determined from Florida voter registration data; and 4) can be 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

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. Female-owned restaurants are 4.2% less likely to receive a PPP loan.

One potential reason why minority-owned restaurants are less likely to receive PPP loans is that they are located in underserved 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

Table 4
Racial Disparities in the Uptake of Emergency Loans

This table reports the results of linear probability model regressions of receiving emergency loans:

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

where f indexes firms, r indexes restaurants and z indexes ZIP codes. The sample construction is summarized in Tables 1 and 2. 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			✓	✓			✓	✓

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 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. Since Black-owned restaurants tend to be in ZIP codes with lower branch density, lower household income, and more COVID cases per capita, the estimated magnitude of the disparity in PPP uptake for Black-owned restaurants 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 the estimated disparity 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 the estimated disparity for Hispanic-owned restaurants, reducing the magnitude of the 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, the disparity for Black-owned restaurants remains large and statistically significant despite the inclusion of ZIP code fixed effects. The estimated disparity for Hispanic-owned restaurants is smaller but still statistically significant.

We next consider whether restaurant characteristics affect PPP loan demand and supply. Thus, in column 4 we add firm age and size controls, using the log number of restaurant seats as a proxy for size. We also add a variety of restaurant characteristics from Yelp, all measured before the 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 before 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. The second is that these characteristics could control for loan supply as PPP lenders may have prioritized larger, more established and popular restaurants. This could be because they were more likely to be existing customers of the lender. It is also possible that lenders prioritized them because there were more fees from making larger PPP loans or because these restaurants were more likely to survive and become future customers of the lender.

Importantly, controlling for the firm characteristics described above 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. These estimated disparities 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 rates of PPP borrowing by Black- and Hispanic-owned restaurants are driven by lower rates of PPP borrowing from banks. 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%. Still, the effect remains large and statistically significant. For Hispanic-owned restaurants, the difference is 3.5%, and Asian-owned restaurants—which exhibit no disparity in overall PPP uptake—were 6.7% less likely to receive a PPP loan from a bank. There is no statistically significant disparity in bank PPP borrowing for female-owned restaurants.

Columns 1–4 of Panel B in Table 4 tell a very different story for PPP loans made by nonbanks. The regressions indicate that for minority-owned restaurants borrowing from nonbanks tends to offset the lower rate of bank PPP borrowing, 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 uptake 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 this is not the case for Black-owned restaurants, which have lower rates of overall PPP uptake. The restaurant controls also indicate that smaller and younger restaurants substitute away from banks, which tend to lend more to larger and older firms.

In columns 5–8 of Panel B, we present results on the determinants of EIDL borrowing. As noted above, firms applied for EIDL loans directly through the SBA website. They could apply for and receive loans from both PPP and EIDL at the same time, though the proceeds had to 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 are more likely to receive emergency loans from nonbanks and the EIDL program suggests that lower demand for emergency loans by minority-owned restaurants does not explain racial disparities in bank PPP lending. In Section 6, we more fully examine the possibility that our findings are explained by minority-owned restaurants having lower demand for emergency loans. For example, minority-owned restaurants may have had lower demand for PPP loans because they were more likely to shut down during the pandemic or were operating at reduced capacity relative to white-owned restaurants. This might be the case if minority-owned restaurants were less profitable going into the pandemic or were more likely to serve minority populations more adversely affected by the pandemic. It is also possible that minority-owned restaurants were less aware of emergency support programs or were less willing to apply to such programs. We present a variety of results that allow us to reject these alternative explanations.

Before analyzing whether bank relationships and racial bias could help explain racial disparities, we note that our findings are robust to a number of alternative sample specifications. In columns 1 and 4 of the Internet Appendix Table IA1, we restrict the sample to single-restaurant firms, which comprise 93% of the sample.[14] We find very similar results for PPP loans (column 1) and bank PPP loans (column 4). In columns 2 and 5, we redefine the dependent variable to be equal to one if either the firm or any of its affiliates receives a bank PPP loan. We consider two firms to be affiliated if they have the same first officer.[15] We find somewhat stronger results when incorporating information about PPP loans received by affiliates. Finally, in columns 3 and 6 we examine robustness to using fixed effects for Census block groups, a much more granular geography than a ZIP code. This regression is meant to address the concern that minority-owned restaurants may have been located farther away

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

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

from bank branches or may have been subject to different shocks even with a ZIP code.[16] We find similar results when comparing minority- and white-owned restaurants within these more narrowly defined geographic areas.

4 Bank Relationships

This section explores the role that bank relationships could play in explaining racial disparities in PPP borrowing. If banks prioritized businesses with which they had strong relationships, and minority-owned businesses had relatively weak relationships with banks, then we would expect to see racial disparities in bank PPP borrowing 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 all aspects of a restaurant's banking relationships, restaurants in the sample likely have some kind of banking relationship because 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 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 outstanding bank loans. Although we cannot observe all of a firm's loans, we can observe secured loans except those 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 are 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 borrow with credit cards 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.

[16] We obtain 2010 Census block information from the Census geocoder and Texas A&M GeoServices. Because the Census geocoder has weak coverage of non-residential addresses, we first run restaurant addresses through the 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.

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 banks and nonbanks. Lenders file these financing statements to assert their security interest in a loan. The security interest could be in physical capital, such as equipment, or 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 Black-owned restaurants that have UCC loans with banks (6%) is considerably lower than it is for white-owned restaurants (20%), although the percentages are quite similar for loans from nonbanks (14%).

Table 5
UCC Borrowing 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 borrowing relationships. The sample construction is summarized in Tables 1 and 2. Controls include all restaurant characteristics included in the regression in column 4 of Table 4. 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***	−0.144***
	(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***	0.072***		0.077***	0.101***
		(0.012)	(0.019)		(0.013)	(0.021)
Nonbank UCC loan		0.054***	0.077***		0.024*	0.034*
		(0.012)	(0.017)		(0.014)	(0.019)
Black × Bank UCC loan			−0.182*			−0.253**
			(0.100)			(0.099)
Black × Nonbank UCC loan			−0.097			0.015
			(0.076)			(0.079)
UCC bank's PPP intensity			0.004			0.006
			(0.006)			(0.006)
R^2	0.179	0.183	0.188	0.191	0.195	0.199
ZIP FEs	✓	✓	✓	✓	✓	✓
Controls		✓	✓		✓	✓
Controls × UCC			✓			✓

(Continued)

The dependent variable in the first three columns of Table 5 Panel A is whether the

Table 5—*continued*

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*	0.049
	(0.019)	(0.019)	(0.021)	(0.029)	(0.029)	(0.031)
Hispanic	0.003	0.002	0.003	0.042***	0.043***	0.041**
	(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*	0.055*
	(0.015)	(0.015)	(0.017)	(0.027)	(0.027)	(0.030)
Female	0.010*	0.010	0.005	−0.005	−0.002	0.003
	(0.006)	(0.006)	(0.007)	(0.011)	(0.011)	(0.013)
Bank UCC loan		−0.024***	−0.029***		0.054***	0.091***
		(0.006)	(0.010)		(0.014)	(0.025)
Nonbank UCC loan		0.030***	0.043***		0.108***	0.139***
		(0.008)	(0.012)		(0.015)	(0.022)
Black × Bank UCC loan			0.071			0.171
			(0.076)			(0.122)
Black × Nonbank UCC loan			−0.112**			−0.079
			(0.046)			(0.083)
UCC bank's PPP intensity			−0.002			−0.023***
			(0.003)			(0.008)
R^2	0.109	0.112	0.115	0.100	0.107	0.111
ZIP FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Controls × UCC			✓			✓

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 the likelihood of not receiving a PPP loan by about 18%.

Controlling for secured borrowing relationships does not affect 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.

Given these findings, it is not surprising that UCC borrowing relationships increase the likelihood of receiving a PPP loan from a bank. As shown in column 5 of the table, 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 almost no effect on the Black-owned restaurant dummy and has only a very modest effect on the coefficients of the other minority-owned restaurant dummies.

Why doesn't controlling for secured borrowing relationships have a bigger effect on estimated disparities? We would expect a more significant reduction in estimated disparities given that borrowing relationships increase the likelihood that a restaurant receives a PPP loan and minority-owned restaurants are much less likely to have these relationships.[17] However, this assumes that bank borrowing relationships have the same effect on PPP uptake for white-owned and minority-owned restaurants. One potential reason why the effects could be different is that minority-owned restaurants may have had relationships with banks that were less active PPP lenders and thus had to find other banks from which to receive PPP loans. To examine this possibility, we look at whether the banks from which white-owned restaurants have outstanding UCC loans were more active PPP lenders than those from which Black-owned restaurants have these types of loans. We measure a bank's PPP lending intensity as the number of PPP loans it extended to Florida firms divided by the number of Florida UCC loans it has outstanding as of February 15, 2020. The average PPP lending intensity is 1.59 for banks of white-owned restaurants and 1.53 for banks of Black-owned restaurants. The difference is not statistically significant. If we include the bank's PPP lending intensity in the PPP and bank PPP regressions for those restaurants with outstanding UCC loans, the coefficient on the lending intensity variable is positive but not statistically significant, as shown in columns 3 and 6 in Table 5.

Another potential reason why controlling for borrowing relationships has a limited effect

[17] 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 disparity in PPP uptake by Hispanic-owned restaurants to fall by 0.77%; in fact, it falls by only 0.20%.

on estimated disparities is that bank 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 with their bank relationships and, as a result, are less likely to apply for a PPP loan from a bank.

We examine these explanations in Table 5 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 5. These estimates are available in the Internet Appendix Table IA4. We also include interactions between the bank UCC loan dummy and restaurant characteristics because restaurant characteristics vary by racial and Hispanic identity and may independently affect whether prior bank borrowing is related to PPP borrowing from banks. In the bank PPP regression shown in column 6, the estimated coefficients of the bank UCC loan variable interactions with 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 25.3% less for Black-owned restaurants than it is for white-owned restaurants. Given that white-owned restaurants with outstanding bank loans are 10.1% 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 15.2% less likely than those without them to get bank PPP loans, although this combined effect is not statistically significant. Nevertheless, we can conclude 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 borrowing relationships or because Black business owners are more dissatisfied with their bank relationships and thus less willing to apply to their bank for a PPP loan.

Importantly, the coefficients of the minority restaurant-owner dummies in the regression in column 6 also tell us that disparities in bank PPP borrowing exist even within the subsample of restaurants that do not have bank borrowing relationships, which comprises well over 80% of the sample. The regression implies, for example, that a Black-owned restaurant without a bank borrowing relationship is still 14.4% less likely to receive a bank PPP loan than a white-owned restaurant without such a relationship. This disparity is modestly less than the estimated 16.6% disparity in column 4, which does not control for bank borrowing relationships. Thus, we conclude that estimated disparities in bank PPP borrowing are not driven by a failure to control for prior bank borrowing relationships. The estimated disparities between minority-owned and white-owned restaurants are large and statistically significant if neither has a bank borrowing relationship; they are even larger if both have a bank borrowing relationship.

Columns 1–3 of Table 5 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 bank borrowing 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 outstanding nonbank loans are more likely to receive nonbank PPP loans suggests that these nonbank relationships also help restaurants access PPP loans.

The coefficients of the interaction terms between *Black* and the UCC loan variables are reported in column 3. The results are consistent with our finding above showing that Black-owned restaurants are less likely than white-owned restaurants to receive a bank PPP loan when they have a bank borrowing relationship. It is thus not surprising that this regression implies that Black-owned restaurants are more likely to receive a nonbank PPP loan, as suggested by the positive coefficient on the interaction of *Black* with the bank UCC loan variable. Of greater interest is the negative, statistically significant coefficient of the interaction of *Black* with the nonbank UCC loan variable. This finding suggests that Black-owned businesses are less likely than white-owned businesses to access nonbank PPP loans because of their nonbank borrowing relationships. This could be because they have weaker relationships with nonbank lenders or because their relationships are with nonbank lenders that are less likely to participate in PPP. 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 than fintech lenders to participate in PPP.

Columns 4–6 of Panel B examine the effect of borrowing relationships on EIDL loans. In column 5, the coefficients on bank and nonbank UCC loans are positive and highly statistically significant. The positive coefficients of UCC borrowing relationship variables in this regression likely reflect greater demand for credit as EIDL loan proceeds can be used to make payments on firms' existing debt. Neither interaction term is statistically significant.

5 Racial Bias

In this section, we look at the effect of racial bias on PPP borrowing. Specifically, we ask whether minority-owned restaurants are less likely to receive PPP loans in locations wit more racial bias in the white population. We use data on explicit and implicit racial bias collected by Project Implicit.[18] 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 an individual's implicit preference for white over Black people.[19] 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."

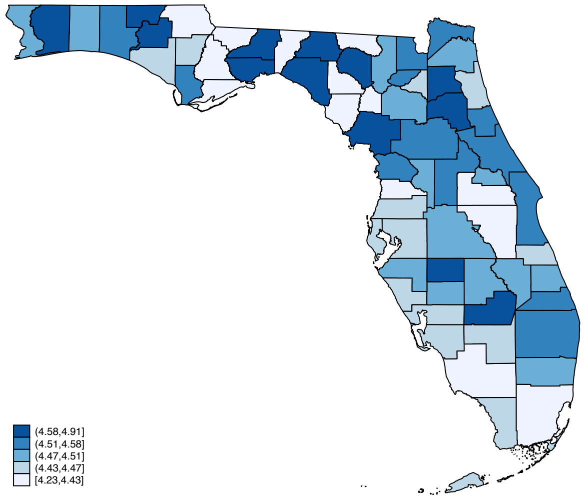
Implicit bias has been shown to be associated with discriminatory behavior. Glover, Pallais, and Pariente (2017) show that the implicit bias of grocery store managers affects the performance of minority cashiers. On days when they are supervised by biased managers, minority cashiers are more likely to 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 averages 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 more substantial 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.

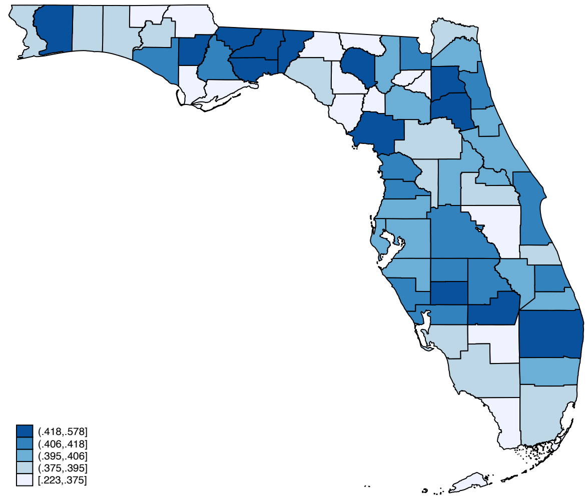
Table 6 reports the results of linear probability models for PPP loans and bank PPP loans in Panel A, and nonbank PPP loans and EIDL loans in Panel B. The main variables of interest are the minority restaurant-owner dummies and their interactions with county-level explicit and implicit bias. Odd-numbered 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 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, we weight

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

[19] Project Implicit also offers a 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 far 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.

observations by the number of responses in the county. Equal weighted regressions generate slightly weaker results. Standard errors are clustered 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 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 PPP loan from a bank. In both regressions, the interaction between *Black* and *Bias* 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%

Table 6
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. The sample construction is summarized in Tables 1 and 2. Controls include all restaurant characteristics included in the regression in column 2 of Table 5. 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**	0.063**	0.062***
	(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***	0.013	0.003
	(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	0.051*	0.052**
	(0.029)	(0.023)	(0.030)	(0.027)	(0.016)	(0.023)	(0.029)	(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**	0.099	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	0.006	0.024
	(0.052)	(0.056)	(0.062)	(0.069)	(0.014)	(0.016)	(0.038)	(0.037)
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)	(0.085)	(0.100)
Other × Bias	−0.213***	−0.253***	−0.147	−0.215**	−0.066	−0.038	−0.004	0.015
	(0.054)	(0.086)	(0.089)	(0.097)	(0.060)	(0.082)	(0.050)	(0.086)
Female × Bias	0.004	0.003	−0.021	−0.025**	0.024*	0.028	−0.015	−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	✓	✓	✓	✓	✓	✓	✓	✓

(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.[20] 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

[20] 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.

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 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 bank PPP borrowing in these counties, which is why the interaction terms in columns 1 and 2 are essentially zero. However, there is still a disparity in PPP borrowing between Black- and white-owned restaurants in the average county.

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 in a way that may explain differences in borrowing and drive the results in Table 6. Table IA3 in the Internet Appendix addresses this concern by adding the interactions of *Black* with various county characteristics, including population, white population share, and existing differences between Black and white individuals in education, unemployment, and household income. We find that Black-owned restaurants are more likely to get PPP loans in more populous counties and in counties with a smaller gap in education. Nevertheless, these regression results indicate that the basic conclusions in Table 6 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. Thus, the estimated coefficient of the racial bias interaction likely reflects biases in the PPP loan process rather than pre-existing differences that may be correlated with racial bias.

To check on the validity of this general approach to measuring bias, we examine whether implicit gender bias is associated with lower uptake 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. Internet Appendix Table IA2 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 female-owned restaurants are more likely to tap nonbank sources of PPP loans in these more gender-biased counties. The results lend support to the idea that the racial bias measure we use is measuring a sentiment towards Black business owners that could bias lending decisions.

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 SBA 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 7, which use data running from January 12 through June 30, 2021, suggest that there was some attenuation in the estimated racial disparity for Black-owned restaurants, particularly in more racially biased counties. Columns 1–2 report the results for PPP loans, columns 3–4 report the results for bank PPP loans, 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 6 and Table 7, both of which report results using the explicit bias 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 6.3% less likely to receive a bank PPP loan in the third round of PPP. The reduction in the estimated disparity is somewhat smaller using the implicit bias measure—a drop from 16.8% to 9.6%. Moreover, unlike the first two rounds of PPP, in the third round, Black-owned restaurants are no less likely to receive PPP loans in more racially biased counties. In fact, the estimates suggest that Black-owned restaurants are more likely to receive PPP loans in these more racially biased counties. This may be because these are the counties where Black-owned restaurants had more pent-up demand for PPP loans given their lower PPP uptake in the first two rounds. This pent-up demand may have been met in the third round because of the measures taken to enhance access by underserved businesses.

Table 7
Round 3 of PPP

This table reports the results of linear probability model regressions of the uptake of PPP loans during the third round of the program from January 12 through April 30, 2021. The sample construction is summarized in Tables 1 and 2. Controls include all restaurant characteristics included in the regression in column 2 of Table 5. *, **, 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	−0.013	−0.078***	−0.063*	−0.096***	0.050**	0.018
	(0.048)	(0.026)	(0.037)	(0.017)	(0.019)	(0.015)
Hispanic	−0.039*	−0.022	−0.052***	−0.022	0.013	−0.000
	(0.021)	(0.015)	(0.017)	(0.016)	(0.014)	(0.009)
Asian	0.018	−0.001	−0.032	−0.040***	0.050***	0.039***
	(0.022)	(0.012)	(0.024)	(0.012)	(0.018)	(0.012)
Other	−0.008	−0.033	−0.055***	−0.079***	0.047*	0.046**
	(0.037)	(0.029)	(0.020)	(0.016)	(0.027)	(0.021)
Female	−0.011	−0.020	−0.032**	−0.034***	0.022***	0.014***
	(0.016)	(0.013)	(0.014)	(0.012)	(0.006)	(0.002)
Black × Bias	0.154**	0.226***	0.074	0.133***	0.079***	0.094***
	(0.072)	(0.039)	(0.064)	(0.043)	(0.021)	(0.024)
Hispanic × Bias	−0.038	−0.036	−0.070	−0.076	0.032*	0.040
	(0.056)	(0.061)	(0.051)	(0.060)	(0.018)	(0.028)
Asian × Bias	0.045	0.070**	0.018	0.056	0.027	0.014
	(0.040)	(0.032)	(0.040)	(0.042)	(0.021)	(0.027)
Other × Bias	0.063	0.045	0.060*	0.045	0.002	0.000
	(0.073)	(0.091)	(0.035)	(0.030)	(0.054)	(0.068)
Female × Bias	0.023	0.049**	0.005	0.016	0.019*	0.033***
	(0.021)	(0.021)	(0.020)	(0.021)	(0.010)	(0.012)
R^2	0.161	0.161	0.164	0.164	0.091	0.090
ZIP FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

6 Alternative Explanations

As previously noted in Section 3 above, an alternative explanation of our core finding of disparities in PPP uptake is that, despite our best efforts, we have not adequately controlled for differences in firm characteristics that could affect the demand for PPP loans. This alternative explanation is inconsistent with the finding that minority-owned businesses make greater use of nonbank PPP loans and EIDL loans. It also cannot explain the lower uptake of bank PPP loans by Black-owned restaurants in more racially biased counties, combined with the greater substitution to nonbank PPP loans and EIDL loans in those counties. Nevertheless, to further and more directly address any remaining concerns, this section explores whether minority-owned restaurants had lower demand for emergency loans. We first examine whether observable differences between minority- and white-owned restaurants during the pandemic could have driven a difference in the demand for emergency loans. We then restrict the sample to restaurants with demonstrated demand for emergency support to see whether the estimated disparities exist within this subsample. Both approaches suggest that differential demand cannot explain our findings.

6.1 Observable Differences in Demand for PPP Loans

In this section, we examine the hypothesis that minority-owned restaurants had lower demand for PPP loans by exploring the most plausible mechanisms that could have driven lower demand. In particular, minority-owned restaurants may have been more likely to shut down during the pandemic or operate at reduced capacity relative to white-owned restaurants. This might be the case if minority-owned restaurants were less profitable going into the pandemic or were more likely to serve minority populations more adversely affected by the pandemic.

Table 8 tries to address this concern in a number of ways. In this table, we include as additional controls several measures of restaurant activity during the pandemic to see whether they could help explain racial disparities. Note that while activity levels may explain PPP borrowing, it is also possible that PPP borrowing could explain activity levels, as a PPP loan could help a restaurant stay in business. Thus, including pandemic activity levels could lead us to underestimate racial disparities in PPP borrowing.

Our first measure of restaurant activity is the natural log of one plus the number of Yelp reviews posted during the pandemic, specifically between March 11, 2020, when the World Health Organization declared COVID a pandemic, and August 8, 2020, when the second round of PPP closed. Restaurants with more reviews are more likely to receive PPP loans and bank PPP loans but are less likely to receive nonbank PPP loans and EIDL loans, as seen in columns 1 and 5 in Panels A and B of Table 8. These regressions also include the full set of controls shown in column 4 of Table 4. Recall that these controls include measures of pre-pandemic activity, such as the number of pre-pandemic restaurant reviews. Notably, while this finding indicates that more active restaurants are more likely to receive bank PPP funding, this control has no meaningful effect on the estimated coefficients of the minority-owned restaurant variables.

Our second measure of restaurant activity during the pandemic is the natural log of one plus the number of average monthly restaurant visits. These data come from SafeGraph,

Table 8
Controlling for Activity during the Pademic

This table shows the robustness of the results to controlling for restaurant activity during the pandemic and to excluding restaurants that closed permanently. The sample construction is summarized in Tables 1 and 2. Ln(Reviews during pandemic) is the natural log of one plus the number of Yelp reviews posted between March 11 and August 8, 2020. Ln(Visits during pandemic) is the natural log of one plus the average number of monthly visits during March–July 2020. Ln(Visits before pandemic) is the natural log of one plus the average number of monthly visits during October 2019–February 2020. Monthly visits are from SafeGraph. Controls include all restaurant characteristics included in the regression in column 2 of Table 5. 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.

Panel A: PPP and Bank PPP

	PPP				Bank PPP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	−0.114***	−0.100***	−0.114***	−0.126***	−0.171***	−0.169***	−0.177***	−0.174***
	(0.029)	(0.029)	(0.030)	(0.033)	(0.028)	(0.028)	(0.029)	(0.033)
Hispanic	−0.031**	−0.029*	−0.031**	−0.028*	−0.032**	−0.030*	−0.030*	−0.029*
	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)	(0.017)
Asian	0.011	0.016	0.013	0.012	−0.063***	−0.056***	−0.060***	−0.066***
	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.018)	(0.018)	(0.019)
Other	−0.005	−0.002	−0.001	−0.012	−0.035	−0.027	−0.024	−0.044
	(0.025)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
Female	−0.005	−0.007	−0.008	−0.009	−0.016	−0.020*	−0.022*	−0.025**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Ln(Reviews during pandemic)	0.013*		0.009	0.006	0.027***		0.022***	0.020**
	(0.008)		(0.008)	(0.009)	(0.008)		(0.008)	(0.009)
Ln(Visits during pandemic)		0.035**	0.001	−0.006		0.032**	0.001	−0.005
		(0.015)	(0.016)	(0.018)		(0.015)	(0.016)	(0.019)
Ln(Visits before pandemic)		−0.025*	0.006	0.014		−0.021	0.007	0.013
		(0.015)	(0.016)	(0.018)		(0.015)	(0.016)	(0.018)
N	9,736	9,297	9,082	8,213	9,736	9,297	9,082	8,213
R^2	0.180	0.185	0.183	0.181	0.192	0.198	0.195	0.191

(Continued)

which collects anonymous data on visits to points of interest using cell phone tracking.[21] We also include the average number of monthly visits to the restaurant before the pandemic as another control for pre-pandemic profitability. Columns 2 and 6 in both panels confirm the finding that restaurant activity during the pandemic is associated with a higher likelihood of receiving PPP funding from banks, but it does not affect the estimated coefficients of the minority-owned restaurant variables. Columns 3 and 7 use both measures of restaurant activity during the pandemic, namely Yelp reviews and restaurant visits. Neither measure is statistically significant, likely because of multicollinearity, but estimated racial disparities are not materially affected.

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

Table 8—*continued*

Panel B: Nonbank PPP and EIDL								
	Nonbank PPP				EIDL			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	0.057***	0.069***	0.063***	0.049**	0.045	0.043	0.034	0.043
	(0.020)	(0.021)	(0.021)	(0.022)	(0.030)	(0.031)	(0.032)	(0.035)
Hispanic	0.000	0.001	−0.001	0.001	0.040**	0.039**	0.035**	0.035**
	(0.008)	(0.008)	(0.008)	(0.009)	(0.016)	(0.016)	(0.017)	(0.018)
Asian	0.073***	0.073***	0.072***	0.078***	0.018	0.026	0.022	0.015
	(0.011)	(0.012)	(0.012)	(0.013)	(0.018)	(0.018)	(0.018)	(0.020)
Other	0.030**	0.026*	0.023	0.032**	0.046*	0.056**	0.049*	0.036
	(0.015)	(0.015)	(0.015)	(0.016)	(0.027)	(0.027)	(0.027)	(0.028)
Female	0.011*	0.013**	0.014**	0.016**	−0.006	−0.008	−0.012	−0.018
	(0.006)	(0.006)	(0.006)	(0.007)	(0.011)	(0.012)	(0.012)	(0.013)
Ln(Reviews during pandemic)	−0.014***		−0.013***	−0.014***	−0.036***		−0.033***	−0.039***
	(0.004)		(0.004)	(0.005)	(0.008)		(0.009)	(0.010)
Ln(Visits during pandemic)		0.004	−0.000	−0.001		−0.019	−0.030*	−0.048**
		(0.007)	(0.008)	(0.009)		(0.016)	(0.018)	(0.019)
Ln(Visits before pandemic)		−0.004	−0.000	0.001		0.012	0.022	0.037**
		(0.007)	(0.008)	(0.008)		(0.016)	(0.017)	(0.019)
N	9,736	9,297	9,082	8,213	9,736	9,297	9,082	8,213
R^2	0.115	0.116	0.119	0.128	0.113	0.116	0.121	0.131
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Exclude closed restaurants				✓				✓

Finally, in columns 4 and 8 of both panels we again include the above measures of restaurant activity during the pandemic, but we exclude restaurants that closed after the pandemic began. We consider a restaurant to have permanently closed if at least 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. According to these criteria, about 11% of restaurants in our data have permanently closed or changed ownership since the pandemic. Restricting the analysis to this sample does not materially affect estimated racial disparities.

6.2 Unobservable Differences in Demand for PPP Loans

Although our regression specifications control for an extensive set of observable restaurant characteristics—both before and during the pandemic—there are possibly unobservable differences in demand that could help explain racial disparities in PPP borrowing. One possibility is that minority-owned restaurants were less aware of PPP. Indeed, in a survey conducted by the Federal Reserve, 20% of Black-owned businesses cited a lack of awareness of PPP as a reason why they did not apply; only 7% of white-owned non-applicants cited this reason (Federal Reserve Banks, 2021). Another possibility is that minority-owned restaurants may have had fewer employees even controlling for location and restaurant activity. Since the size of a PPP loan is based on payroll, restaurants with fewer employees receive smaller loans and thus may have found that the costs of applying for PPP outweighed the benefits.

We address these concerns by exploiting data on the EIDL Advance program.[22] The EIDL Advance program provided grants of $1,000 per employee, up to 10 employees. About half of the restaurants in our sample received EIDL Advance grants. These restaurants were obviously aware of the EIDL program and thus very likely to have been aware of other emergency relief programs like PPP. Furthermore, because these restaurants had all the paperwork necessary to apply for an EIDL loan and to qualify for an EIDL Advance grant, their marginal cost of applying for PPP should have been minimal. At the same time, at $1,000 per employee, EIDL Advance grants were very modest compared to PPP, which provided forgivable loans of 2.5 times monthly employee wages. PPP loans would exceed the size of the EIDL Advance grant provided a worker earned more than $400 per month, a very modest amount. Indeed, 80% of firms that received an EIDL Advance grant also applied for and received a PPP loan.[23] Thus, by examining racial disparities in PPP borrowing among restaurants that received EIDL Advance grants, our analysis focuses on a sample of firms that wanted emergency loans and were aware of their availability.

Restricting the sample to EIDL Advance recipients has the added benefit of allowing us to control for the number of employees, which should be closely correlated with payroll. Because the grant size is $1,000 times the number of employees up to $10,000, we can back out the number of employees up to 10. Because EIDL Advance grants are capped at $10,000, we include a dummy variable for firms with at least ten employees. As an alternative approach, we restrict the sample to firms with fewer than 10 employees.

Table 9 reports the results of linear probability model regressions of receiving PPP (columns 1–2), bank PPP (columns 3–4), and nonbank PPP loans (columns 5–6), conditional on receiving an EIDL Advance grant. Column 1 of Table 9 repeats the baseline specification in column 4 of Table 4, but also includes the number of employees implied by the EIDL Advance grant up to 10 and a dummy variable for whether the EIDL Advance grant was the maximum amount of $10,000. An additional employee is associated with a 5.4

[22] https://data.sba.gov/dataset/covid-19-eidl-advance.

[23] An EIDL Advance grant would count against the forgivable portion of the PPP loan.

Table 9

PPP Borrowing Conditional on Receiving EIDL Advance

In this table we restrict the sample to restaurants that received EIDL Advance grants and use grant size as a proxy for the number of employees. The EIDL Advance program provided grants of $1,000 per employee up to a maximum of $10,000. Odd-numbered columns include a dummy for firms with 10 or more employees, i.e., firms receiving EIDL Advance grants of $10,000. Even-numbered columns exclude firms receiving EIDL Advance grants of $10,000. The sample construction is summarized in Tables 1 and 2. Controls include all restaurant characteristics included in the regression in column 2 of Table 5. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	PPP		Bank PPP		Nonbank PPP	
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.164***	−0.137**	−0.257***	−0.216***	0.093***	0.079*
	(0.040)	(0.058)	(0.039)	(0.055)	(0.031)	(0.042)
Hispanic	−0.038**	−0.040	−0.019	−0.049	−0.019*	0.009
	(0.018)	(0.037)	(0.020)	(0.038)	(0.011)	(0.021)
Asian	0.018	0.034	−0.060***	−0.063*	0.078***	0.097***
	(0.019)	(0.033)	(0.022)	(0.036)	(0.016)	(0.024)
Other	−0.023	−0.049	−0.068**	−0.119**	0.046*	0.070*
	(0.030)	(0.055)	(0.032)	(0.055)	(0.024)	(0.040)
Female	−0.011	−0.006	−0.027*	−0.035	0.017*	0.029*
	(0.014)	(0.025)	(0.015)	(0.027)	(0.010)	(0.017)
Num. employees	0.054***	0.051***	0.055***	0.052***	−0.001	−0.001
	(0.004)	(0.005)	(0.005)	(0.006)	(0.003)	(0.004)
I(Num. employees $\geq$ 10)	−0.097***		−0.098***		0.001	
	(0.025)		(0.027)		(0.017)	
N	4,935	2,141	4,935	2,141	4,935	2,141
R^2	0.320	0.388	0.323	0.381	0.193	0.314
ZIP FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Exclude firms with $\geq$ 10 employees		✓		✓		✓

percentage point greater probability of receiving a PPP loan, but beyond 10 or more employees there is no incremental increase in the likelihood of receiving a PPP loan. Notably, the disparities in PPP uptake remain large: Black-owned restaurants are 16.4% less likely to receive PPP loans controlling for the number of employees.

Columns 3 and 5 show that PPP uptake is increasing in the number of employees. This effect is driven by a positive relationship between bank PPP loans and the number of employees. This is not the case for nonbank PPP loans, suggesting that the relationship between PPP uptake and the number of employees is likely driven by the supply of bank PPP loans rather than by the demand for PPP funding. The even-numbered columns further restrict the sample to firms with fewer than 10 employees. The results in these columns are similar to those in the odd-numbered columns.

Finding racial disparities in PPP borrowing in the subsample of EIDL Advance participants shows that racial disparities in PPP cannot be explained by lower demand for emergency support by minority-owned businesses or less awareness of such support programs. Another way to establish this is to look at the subsample of restaurants that receive EIDL or PPP loans. Similar to our analysis of EIDL Advance program participants, we can ask whether there are racial disparities in PPP uptake among the sample of firms that receive EIDL or PPP loans. These restaurants have a demonstrated demand for emergency loans and an awareness that such programs exist. In Table 10, we find that there are racial disparities in PPP uptake within this subsample of firms, with Black- and Hispanic-owned restaurants both significantly less likely to receive PPP loans. As before, the disparities are driven by disparities in bank borrowing. Minority-owned restaurants are less likely to borrow from banks even controlling for ZIP code and restaurant characteristics. In particular, Black-owned restaurants receiving an emergency loan are 21.3% less likely than white-owned restaurants to receive a PPP loan from a bank. This finding further supports the view that unobserved differences across groups in emergency loan demand or loan awareness do not explain disparities in PPP borrowing.

Table 10
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 5. 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***	−0.101***	−0.330***	−0.275***	−0.213***
	(0.027)	(0.030)	(0.029)	(0.032)	(0.035)	(0.034)
Hispanic	−0.074***	−0.058***	−0.050***	−0.088***	−0.067***	−0.052***
	(0.010)	(0.011)	(0.011)	(0.012)	(0.014)	(0.014)
Asian	−0.014	−0.010	−0.001	−0.120***	−0.114***	−0.094***
	(0.010)	(0.011)	(0.011)	(0.016)	(0.017)	(0.017)
Other	−0.047***	−0.036*	−0.026	−0.099***	−0.083***	−0.068***
	(0.018)	(0.019)	(0.019)	(0.024)	(0.025)	(0.024)
Female	−0.023***	−0.023***	−0.010	−0.041***	−0.039***	−0.022**
	(0.008)	(0.008)	(0.008)	(0.010)	(0.011)	(0.010)
R^2	0.023	0.145	0.184	0.040	0.161	0.200
ZIP FEs		✓	✓		✓	✓
Controls			✓			✓

7 External Validity

One may wonder whether the results apply to other industries since restaurants were hit especially hard by the pandemic. Because we cannot identify the population of potential borrowers in other industries, we restrict our analysis to firms receiving some form of government support, just as we did in the section above. First, we examine whether there are racial disparities in PPP uptake among the broader sample of Florida firms that receive EIDL Advance grants, just as we did in Table 9 for restaurants. Second, following the basic approach outlined in Table 10 for restaurants, we ask whether minority-owned firms were less likely to receive PPP loans in the sample of firms that received either PPP loans or EIDL loans. For both sets of analyses, we ask whether racial disparities are greater in more racially biased counties.

To create the broader sample, we start by matching PPP, EIDL, and EIDL Advance recipients 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 and 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, EIDL, and EIDL Advance recipients to data from Dun & Bradstreet using information on the firm's name and location. Firm 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 can 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.

Panel A of Table 11 repeats the analysis in Table 9 for a broad set of industries. We explore whether minority-owned businesses that receive EIDL Advance grants are less likely to receive PPP loans after controlling for the number of employees derived from the size of the EIDL Advance grant. 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 the coefficients of minority-owned business dummies without

Table 11
PPP Borrowing Conditional on Receiving EIDL Advance: All Industries

This table reports the results of linear probability model regressions of receiving PPP loans conditional on receiving EIDL Advance. The sample consists of all firms that receive EIDL Advance that can be matched to Florida corporate records, voter registration, and Dun & Bradstreet. Panel A reports the results of regressions with different controls. Panel B reports the results of regressions that include the interaction between *Black* and racial bias. Panel B regressions include all controls used in column 3 of Panel A; their coefficients are not reported for brevity. Industry classification and sales are from Dun & Bradstreet. Number of employees is estimated using the size of EIDL Advance. 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.

Panel A: Baseline

	PPP				Bank PPP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	−0.194***	−0.128***	−0.091***	−0.081***	−0.247***	−0.178***	−0.139***	−0.121***
	(0.007)	(0.021)	(0.018)	(0.020)	(0.007)	(0.011)	(0.011)	(0.012)
Hispanic	−0.146***	−0.101***	−0.071***	−0.071***	−0.144***	−0.095***	−0.066***	−0.065***
	(0.005)	(0.012)	(0.011)	(0.013)	(0.008)	(0.011)	(0.010)	(0.011)
Asian	0.045***	0.009	0.005	−0.004	0.018*	−0.015	−0.017	−0.022
	(0.010)	(0.017)	(0.016)	(0.020)	(0.010)	(0.017)	(0.016)	(0.020)
Other	−0.057***	−0.055***	−0.033***	−0.033**	−0.067***	−0.066***	−0.043***	−0.042**
	(0.015)	(0.014)	(0.011)	(0.015)	(0.015)	(0.013)	(0.011)	(0.017)
Female	−0.011***	−0.020***	0.005	0.006	−0.012***	−0.018***	0.006	0.007
	(0.004)	(0.006)	(0.006)	(0.007)	(0.004)	(0.007)	(0.006)	(0.007)
Ln(Firm age)			0.044***	0.042***			0.043***	0.041***
			(0.005)	(0.004)			(0.005)	(0.005)
Ln(Sales)			0.053***	0.056***			0.055***	0.056***
			(0.006)	(0.007)			(0.005)	(0.007)
Num. employees			0.061***	0.061***			0.057***	0.057***
			(0.004)	(0.004)			(0.003)	(0.004)
I(Num. employees $\geq$ 10)			−0.188***				−0.164***	
			(0.015)				(0.018)	
Bank UCC loan			0.088***	0.083***			0.107***	0.094***
			(0.014)	(0.013)			(0.012)	(0.012)
Nonbank UCC loan			0.061***	0.061***			0.028**	0.025
			(0.013)	(0.015)			(0.013)	(0.016)
N	93,465	93,465	93,465	81,390	93,465	93,465	93,465	81,390
R^2	0.025	0.556	0.616	0.608	0.031	0.564	0.621	0.613
SIC-ZIP FEs		✓	✓	✓		✓	✓	✓
Exclude firms with $\geq$ 10 employees				✓				✓

Panel B: Interaction with racial bias

	Explicit		Implicit		Explicit		Implicit	
	PPP				Bank PPP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	−0.083***	−0.073***	−0.075***	−0.058***	−0.135***	−0.117***	−0.128***	−0.106***
	(0.019)	(0.020)	(0.022)	(0.020)	(0.011)	(0.010)	(0.016)	(0.014)
Black × Bias	−0.056	−0.079	−0.064	−0.112***	−0.066**	−0.076**	−0.063	−0.090**
	(0.045)	(0.052)	(0.044)	(0.040)	(0.032)	(0.033)	(0.051)	(0.041)
R^2	1	1	1	1	1	1	1	1
SIC-ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Exclude firms with $\geq$ 10 employees		✓		✓		✓		✓

controls for location, industry and firm characteristics. The second column in each block adds ZIP code cross industry fixed effects. The third column in each block adds log firm age, log sales from D&B, number of employees estimated based on the size of the EIDL Advance grant, and prior bank and nonbank UCC loans. The fourth column in each block excludes firms with ten or more employees. As in the restaurant sample, location and firm characteristics explain about half of the disparities in PPP borrowing. The number of employees is positively related to the likelihood of receiving a PPP loan. But as in the restaurant sample, controlling for location and observable firm characteristics, Black-owned firms are still significantly less likely to receive PPP loans. In Panel B of the table we repeat the specification but add the interactions with the racial bias measures. The results indicate that Black-owned restaurants in more racially biased counties are less likely to receive PPP funding.

Table 12 examines whether there are disparities in PPP borrowing and bank PPP borrowing conditional on receiving either PPP or EIDL loans. The first column in each block of regressions estimates minority-owned business dummies without controls for location, industry, and firm characteristics. The second column in each block adds ZIP code and industry fixed effects, while the third column adds industry cross ZIP code fixed effects. Finally, the fourth column in each block adds log firm age, log sales, log number of employees (from D&B), and 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, Panel B examines whether the disparity for Black-owned restaurants is greater in more racially biased counties along the lines of Table 6 for restaurants, but in this broader sample of firms that take out emergency loans. All regressions include ZIP code cross industry fixed effects and the same controls as in Panel A of the table. 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. Our general conclusion is that our findings for restaurants are broadly applicable across a much wider range of industries.

Table 12
Demand for Credit: All Industries

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. Panel A reports the results of regressions with different controls. Panel B reports the results of regressions that include the interaction between *Black* and racial bias. Panel B regressions include all controls used in column 4 of Panel A; their coefficients are not reported for brevity. Odd-numbered regressions in Panel B also control for the interaction of other minority dummies and racial bias; their coefficients are not reported for brevity. 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. $N = 131,372$.

Panel A: Baseline

	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***
	(0.006)	(0.011)	(0.017)	(0.019)	(0.011)	(0.008)	(0.014)	(0.015)
Hispanic	−0.235***	−0.167***	−0.159***	−0.122***	−0.241***	−0.172***	−0.161***	−0.120***
	(0.006)	(0.007)	(0.014)	(0.013)	(0.009)	(0.009)	(0.015)	(0.014)
Asian	−0.023**	−0.027***	−0.030***	−0.005	−0.056***	−0.056***	−0.063***	−0.034***
	(0.010)	(0.008)	(0.011)	(0.011)	(0.011)	(0.009)	(0.012)	(0.011)
Other	−0.108***	−0.088***	−0.091***	−0.064***	−0.128***	−0.102***	−0.113***	−0.081***
	(0.016)	(0.010)	(0.014)	(0.013)	(0.018)	(0.011)	(0.019)	(0.018)
Female	−0.019***	−0.016***	−0.017***	−0.003	−0.027***	−0.021***	−0.022***	−0.006
	(0.003)	(0.002)	(0.006)	(0.006)	(0.003)	(0.002)	(0.004)	(0.005)
Ln(Firm age)				0.062***				0.069***
				(0.004)				(0.004)
Ln(Sales)				0.056***				0.056***
				(0.006)				(0.006)
Ln(Employees)				−0.004				0.006*
				(0.003)				(0.003)
Bank UCC loan				0.076***				0.106***
				(0.006)				(0.007)
Nonbank UCC loan				0.059***				0.028***
				(0.008)				(0.009)
R^2	0.065	0.142	0.520	0.545	0.073	0.150	0.529	0.556
ZIP FEs		✓				✓		
SIC FEs		✓				✓		
SIC-ZIP FEs			✓	✓			✓	✓

Panel B: Interaction with racial bias

	Explicit		Implicit		Explicit		Implicit	
	PPP				Bank PPP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	−0.139***	−0.138***	−0.132***	−0.132***	−0.217***	−0.217***	−0.203***	−0.202***
	(0.020)	(0.020)	(0.025)	(0.023)	(0.017)	(0.017)	(0.026)	(0.023)
Black × Bias	−0.066	−0.067	−0.057	−0.057	−0.114**	−0.116***	−0.117	−0.119**
	(0.054)	(0.045)	(0.063)	(0.051)	(0.056)	(0.035)	(0.074)	(0.054)
R^2	0.518	0.518	0.518	0.518	0.528	0.528	0.528	0.528
SIC-ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Minority × Bias	✓		✓		✓		✓	

8 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 and restaurant characteristics. Past borrowing relationships do little to explain disparities on average. 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 uptake.

Disparities in PPP borrowing are driven by disparities in PPP borrowing from banks. 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 disparity in bank PPP borrowing for Black-owned restaurants appears to be exacerbated by racial bias. Restaurants located in counties where more white people express implicit or explicit biases towards Black people are less likely to receive PPP loans from banks. They are also 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 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 suggest that online, less personalized applications can help mitigate bias. Both fintechs and the SBA used an online application process with relatively less personal interaction than the application process used by many banks.

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 after controlling for differences in restaurant attributes—including proximity to bank branches, age, size and borrowing history—these differences led to substantially lower PPP uptake by minority-owned restaurants. Indeed, these differences explain 60% of the disparity in borrowing by Black- and Hispanic-owned restaurants. While it is possible that some of the attributes of minority-owned restaurants may have lowered their demand for PPP loans, it is also possible that they were impediments to getting PPP loans. Thus, quite apart from issues of racial bias, a program that effectively favored larger businesses in close proximity to banks or with strong 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.

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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.
UCC bank's PPP intensity	Bank's PPP intensity is the ratio of a) PPP loans to Florida-based borrowers to b) UCC loans to Florida-based borrowers that were active as of February 15, 2020. For firms with UCC loans from multiple banks, we calculate the average intensity across banks. For firms without bank UCC loans, itensity is set to zero.
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.

(Continued)

Table A1—*continued*

Variable	**Definition**
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.
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.

Table A2
Nonbank Lenders

This table lists nonbank lenders extending PPP loans to restaurants in our data. Loans held by banks that serve as partner banks to nonbank lenders that originate PPP loans are considered nonbank loans. Cross River Bank, Web Bank and Celtic Bank are the three largest partner banks.

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