

Racial Disparities in the Paycheck Protection Program*

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Abstract

Using a large sample of Florida restaurants, we document significant racial disparities in the utilization of the Paycheck Protection Program (PPP) and investigate the causes of these disparities. Black-owned restaurants are 25% less likely to receive PPP loans. Restaurant location explains 5 percentage points of this differential. Restaurant characteristics gathered from license and Yelp data explain an additional 10 percentage points of the gap in PPP utilization. Prior borrowing relationships do not explain disparities on average. The remaining 10% disparity is driven by a 17% disparity in bank PPP borrowing, which is partially offset by greater borrowing from nonbanks, largely fintechs. This disparity in bank PPP borrowing cannot be attributed to lower demand for emergency loans given that Black-owned restaurants substitute to nonbank sources of PPP loans and to loans from the Economic Injury Disaster Loan (EIDL) program, administered directly by the Small Business Administration (SBA). Moreover, Black-owned restaurants that receive grants from the SBA through the EIDL Advance program are much less likely to get PPP loans compared to otherwise similar white-owned restaurants that receive these grants. Finally, we show that Black-owned restaurants are significantly less likely to receive bank PPP loans in counties in which white people exhibit greater racial bias towards Black people. In these more racially biased counties, Black-owned restaurants substitute more to nonbank PPP loans and EIDL loans. This substitution, however, is not strong enough to eliminate racial disparities in the take-up of PPP loans.

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

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1 Introduction

A key component of the federal government’s response to the negative economic effects of the COVID-19 pandemic was the Paycheck Protection Protection (PPP), authorized by the CARES Act in March 2020 and later extended and enhanced in subsequent legislation. Under PPP, the Small Business Administration (SBA) guaranteed about \$800 billion in low-interest rate loans made by financial institutions to businesses with up to 500 employees, promising to forgive these loans if borrowers maintained employment and certain other fixed expenses. A number of concerns have been raised about the design of this program, including whether it targeted businesses most needing support, whether it was subject to considerable amounts of fraud, and whether it provided equal access to minority-owned businesses.

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

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 utilization 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%. Nonbank PPP lenders—largely fintechs—tend to offset these disparities in bank borrowing by providing loans at greater rates to Black-, Asian- and female-owned restaurants, but not Hispanic-owned restaurants. Except for Asian-owned

¹ Registered voters in Florida are asked to indicate whether they are Black (not of Hispanic origin), Hispanic, White (not of Hispanic origin), Asian/Pacific Islander, American Indian/Alaska native, Multi-racial, or Other. These categories contrast with the current Census designations, which separate the concepts of race and Hispanic origin.

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

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

The first explanation, location, accounts for about 20–30% of the disparity in PPP utilization by minority-owned businesses. Once ZIP code fixed effects are included in regression analyses, 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 effect of ZIP code fixed effects is due to three ZIP code characteristics: bank branches per capita, median household income, and COVID cases per capita. Restaurants in ZIP codes with fewer bank branches per capita, lower household income, and more COVID cases per capita are less likely to get PPP loans.

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

A third explanation for disparities in PPP utilization is that minority-owned firms may have had weaker relationships with banks going into the pandemic. This could explain the findings if banks prioritized their existing clients at a time when banks had limited capacity to process applications. While we cannot measure the entirety of a banking relationship, which could include different types of loans, checking accounts, credit cards, and merchant services, we use data on Uniform Commercial Code (UCC) filings with Florida to determine whether a firm had secured loans outstanding. These loans likely capture the main variation across restaurants in their use of banking services, as almost all of the restaurants in our sample accept credit cards and thus also use business checking accounts and merchant services.

We find that while minority-owned restaurants are much less likely to have bank loans outstanding, controlling for their prior bank borrowing does little to reduce the measured disparities in bank PPP borrowing. There are still large estimated disparities between minority-owned and white-owned restaurants among the large subsample of firms—over 80% of the full sample—that do not have bank borrowing relationships. And while white-owned restaurants gain more PPP access

from bank borrowing relationships, the same is not true of Black-owned restaurants; the estimated disparity between Black- and white-owned restaurants that have a bank borrowing relationship is even larger than it is for the rest of the sample. This finding suggests that banks either do not prioritize Black-owned businesses with which they have borrowing relationships, or that Black business owners are more dissatisfied with their bank lender and thus less likely to apply for a PPP loan from a bank.

The final explanation is that disparities in bank PPP utilization are affected by racial bias, particularly for Black-owned businesses where disparities in bank borrowing are large. It is possible that racial bias exists in the way that banks process PPP loan applications. Indeed, audit studies by the National Community Reinvestment Coalition (NCRC) present evidence that Black, Hispanic and female business owners received worse treatment from banks in response to inquiries about PPP loans ([National Community Reinvestment Coalition, 2020b,a](#)). It is also possible that while there was no discrimination conditional on applying for a bank PPP loan, a legacy of past discrimination and poor treatment may have discouraged minority-owned businesses, particularly Black-owned businesses, from even approaching banks for a PPP loan.

The portion of racial disparities not explained by our extensive controls for location, firm characteristics, and borrowing relationships is arguably attributable to racial bias. 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 Black-owned restaurants are less likely to get PPP loans but are more likely to get EIDL loans than otherwise comparable white-owned restaurants located in the same ZIP code. Nevertheless, to alleviate concerns about unobserved factors and to provide more direct evidence of the role of racial bias, we examine whether racial disparities in bank PPP utilization are greater in counties that appear to be more racially biased. We use measures of implicit and explicit racial bias from Project Implicit, which offers online tests to measure a person’s implicit associations and biases.² Our findings indicate that Black-owned restaurants in counties in which white test-takers exhibit more explicit and implicit bias towards Black people are significantly less likely to receive PPP funding from banks. The effect is large: a one standard deviation increase in explicit bias is associated with a 13.9 percentage-point reduction in the probability that a Black-owned restaurant receives a PPP loan from a bank. Given that a Black-owned restaurant in a county with an average level of explicit racial bias is 22.3% less likely to get a bank PPP loan, this implies that Black-owned restaurants in the more racially biased counties are 36.2% less likely than white-owned restaurant to get a bank PPP loan. The results using the implicit bias measure are similar. Moreover, in more racially biased counties, Black-owned businesses are much more likely to substitute to nonbank PPP lenders and EIDL loans. Both sources of emergency loans typically involve online applications, with less personal interaction than the typical bank application process. This may help to explain why Black business owners substitute to these funding sources.

² <https://implicit.harvard.edu/implicit/takeatest.html>

We also examine whether efforts of the SBA to reduce racial disparities in the third round of PPP—largely by prioritizing lending through financial institutions with closer ties to minority communities—had the intended effect. We show that racial disparities were attenuated, particularly for Black-owned restaurants, although disparities remain. We also find that in the third round racial disparities were not greater in more racially biased counties.

We next explore whether the estimated disparities in PPP utilization could, in part, be explained by lower demand for such loans by minority-owned restaurants and whether our findings generalize beyond restaurants to other industries. On its face, this explanation of disparities is unlikely to have much traction given that minority owned-restaurants substitute from bank PPP loans to nonbank PPP loans and EIDL loans, which demonstrates that they wanted subsidized loans during the pandemic. Nevertheless, it is possible that minority-owned restaurants were hit harder by the pandemic or were more vulnerable to the pandemic and, as a result, were more likely to shut down and thus not apply for bank PPP loans. We do not find that this is the case, however. Controlling for observable characteristics, minority-owned restaurants are not more likely to shut down. Moreover, our findings on a restricted sample of surviving restaurants are similar to our findings on the full sample. Controlling for restaurant visits during the pandemic also does not affect the estimated racial disparities in PPP utilization.

We also address the concern that disparities are driven by lower demand for PPP loans by minority-owned restaurants by examining PPP utilization in a sample of firms that receive EIDL Advance grants, a program that gave businesses \$1,000 for each employee, up to a total of 10 employees. This allows us to more accurately control for the number of employees, and it allows us to analyze PPP utilization in a sample of firms with demonstrated awareness of government emergency support programs and demand for such support. Among firms that receive EIDL Advance grants, we find that Black-owned businesses are significantly less likely to receive PPP loans relative to white-owned businesses with the same number of employees. Moreover, the disparity in bank PPP utilization 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 variation in PPP take-up rates, we can study disparities in PPP loans among the sample of firms that receive EIDL Advance grants. Controlling for ZIP code cross industry fixed effects, firm age, sales, employees, and secured borrowing relationships, minority-owned restaurants are significantly less likely to receive bank PPP loans, and Black- and Hispanic-owned businesses are also significantly less likely to receive PPP loans overall. Moreover, Black-owned businesses are less likely to receive a bank PPP loan in more racially biased counties. We find similar results in a sample of firms that receive EIDL loans or PPP loans; in this sample, minority-owned businesses are less likely to receive PPP loans, and they are less likely to receive them from banks, particularly if the business operates in a more racially biased county.

Our decomposition of racial disparities into four factors—location, firm characteristics, bank relationships, and racial bias—has implications for how we evaluate the design of PPP. In particular, we show that older, larger, more heavily visited and reviewed restaurants with bank borrowing relationships were more likely to receive PPP funding. However, Black-owned restaurants tend to be younger, smaller, less heavily visited and reviewed, and less likely to have bank relationships. Thus, even if there was no racial bias in the implementation of PPP, the program was used less frequently by Black-owned businesses because the features of the program made it less attractive to the types of businesses they own or because lenders found it less desirable to lend to these types of businesses.

Our paper is part of a growing literature studying the functioning and impact of PPP,³ including a number of recent studies on racial disparities in PPP. Wang and Zhang (2020) show that ZIP codes with a greater percentage of Black residents had lower take-up rates of PPP loans, measured by the ratio of PPP loans to the number of establishments in a ZIP code. The lower take-up rate is related to a lower concentration of branches of PPP-approved lenders in ZIP codes with more Black residents. Consistent with this finding, Erel and Liebersohn (2020) document that fintech lenders originated a larger share of PPP loans in ZIP codes with a larger minority population share. While these findings are important in that they suggest that location matters in accessing PPP funding, our firm-level approach allows us to look beyond location, and examine the role of firm characteristics, borrowing relationships, and racial bias. We show that ZIP code fixed effects account for only one fifth of racial disparities in PPP utilization and that firm characteristics, borrowing relationships, and racial bias are much more important in explaining racial disparities.

In a contemporaneous paper 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 than banks. Both Howell et al. (2021) and our paper find that there is greater substitution of Black-owned businesses to fintechs in more racially biased locations and that controlling for prior banking relationships (measured differently) does not meaningfully reduce average disparities in bank PPP funding. All three papers suggest that online loan application processes are associated with less racial disparities in PPP utilization. However, there are a number of distinctive features of our paper. First, and perhaps most importantly, because we focus on restaurants we are able to identify a set of firms that arguably all qualified for PPP. We are thus able to examine the effect of racial bias on the likelihood that a restaurant receives PPP funding, whereas Howell et al. (2021) 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

³ 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).

lenders, the greater availability of this type of funding is not enough to compensate for the lower availability of bank PPP funding. Thus, we can conclude that racial bias has real effects on PPP access. Second, by linking business owners to voter registration data, we have a more accurate measure of race and ethnicity than either the machine learning algorithm used in [Howell et al. \(2021\)](#) or identification of owner’s race based on a restaurant’s 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 the Paycheck Protection Program, our paper contributes to a broader literature on discrimination in small business lending. [Blanchflower, Levine, and Zimmerman \(2003\)](#), [Cavalluzzo and Wolken \(2005\)](#), [Blanchard, Zhao, and Yinger \(2008\)](#), 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 indications of racial bias, consistent with our findings. These studies suggest that our findings could, in part, be driven by a historical legacy of discrimination that discourages Black-owned businesses from applying for PPP loans from banks.

The rest of the paper is organized as follows. Section 2 describes our data and reports basic summary statistics. Section 3 documents the existence of racial disparities in PPP utilization, showing that they are driven by disparities in bank PPP borrowing and that there is partial substitution to nonbank sources of PPP funding. We also document the role of location and restaurant characteristics in explaining racial disparities in PPP utilization. We examine whether differences in bank relationships could explain racial disparities in Section 4 and then examine the role of racial bias in Section 5. Section 6 provides evidence against the view that racial disparities in PPP are 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) restaurant characteristics from Yelp. 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.⁴ 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 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. Most of our analyses, however, compare PPP and EIDL loans extended during 2020. Both PPP and EIDL data report the borrower’s name and location, loan amount, and approval date. PPP loan data also report the lender’s name and location, the borrower’s industry, and self-reported demographic information on the borrower. The vast majority of PPP borrowers (83%), however, do not report information on racial or Hispanic identity.

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

2.2 Potential Borrowers

Much of the existing research on the Paycheck Protection Program is constrained by the limited data on small private firms, which comprise most of the eligible borrowers. We overcome this limitation by studying the utilization of PPP and EIDL loans by Florida restaurants.⁵ 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.⁶

To generate a relatively homogeneous sample, we focus on restaurants that offer seating, while excluding food trucks, takeout-only restaurants without seating, and caterers. We also exclude restaurants with licenses approved after February 15, 2020, hotel restaurants, and franchise restaurants. Because hotel and franchise restaurants are frequently owned and operated by affiliated entities, it can be difficult to determine whether a given hotel or franchise restaurant received an

⁴ 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>

⁵ Restaurants, defined as borrowers with NAICS codes starting with 722, account for 6.4% of all PPP loans.

⁶ <http://www.myfloridalicense.com/DBPR/hotels-restaurants/public-records/>

emergency loan. Even if the license holder did not receive an emergency loan, it is possible that its parent or affiliate did.⁷ To minimize error in determining which restaurants received emergency loans, we exclude hotel and franchise restaurants. Restaurants are classified as being in a hotel if they share the same address as one of the hotels in Florida hotel license data.⁸ 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 are able to match 91% of restaurants that meet the sample selection criteria to Florida corporate records. Most of the remaining restaurants list individuals as license holders and cannot be unambiguously matched to corporate records.

Table 1 summarizes the sample selection criteria and the number of restaurants matched to Florida corporate records. We exclude from the analysis restaurants owned by non-profits, out-of-state firms,⁹ and publicly-traded firms. We also exclude restaurants matched to firms registered for the first time after February 15, 2020.

Table 1
Florida Restaurants Sample

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

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

⁷ In the robustness analyses in Table A5, we use an algorithm to identify affiliated firms and find larger disparities in the take-up of bank PPP loans, when we measure take-up across all of the restaurant’s affiliates.

⁸ <http://www.myfloridalicense.com/DBPR/hotels-restaurants/lodging-public-records/>

⁹ 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.

2.3 Racial and Hispanic Identity of Potential Borrowers

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

Howell et al. (2021) use a machine learning algorithm to predict racial and Hispanic identity in the PPP sample based on the officer’s name and the location of the business. Regression results that use predicted racial or Hispanic identity must be interpreted with caution because measurement error will cause the coefficients on the predicted identity to understate the true effect of racial or Hispanic identity, with the magnitude of bias depending on the relative accuracy with which the algorithm can classify different groups.

In addition to 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 areas, it is possible that the estimated magnitude of disparities in PPP utilization in more racially biased areas is overstated because the racial bias measure 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 or Hispanic identity.¹⁰ Voter registrants can specify whether they identify as one of the following: 1) American Indian or Alaskan Native, 2) Asian or Pacific Islander, 3) Black, not Hispanic, 4) Hispanic, 5) white, not Hispanic, 6) other, or 7) multi-racial. Because of the small number of observations, we 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 and to “Black, not Hispanic” as Black, and “white, not Hispanic” as white. Note that while these classifications are imperfect, in part because they do not separate race from ethnic identity, Ganong et al. (2020) show that there is a 99% agreement rate between the way voters identify themselves in a sample of voter registration files and mortgage applications.

We match the firm’s owner to voter registration data based on name and location. Details of the matching algorithm are provided in the Appendix. Overall, we are able to identify a restaurant owner’s racial or Hispanic identity for 56% of the sample restaurants. In most of these cases, we

¹⁰ <https://dos.myflorida.com/elections/data-statistics/voter-registration-statistics/voter-extract-disk-request/>

have a unique match within a county. If there are multiple potential matches, but they all report the same racial or Hispanic identity, we use what is reported even though we cannot identify the specific voter match.

One further advantage of using voter registration data is that by conditioning on the owner 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 may be more likely to apply.

2.4 Restaurant Characteristics

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

Our version of Yelp data includes information on restaurant features such as whether the restaurant accepts credit cards, offers delivery, or has outside seating. We use features 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

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.

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 classify them as bank or nonbank. For each restaurant in our sample, we then check whether the firm had an active UCC filing and whether the underlying loan was with a bank or a nonbank.

2.7 Summary Statistics

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

3 Documenting Disparities

Table 3 reports data on restaurant characteristics, locations, and emergency loan utilization for restaurants owned by the various demographic groups. Minority-owned restaurants and restaurants owned by women tend to be younger and smaller. They are also less likely to have an existing secured loan with either a bank or nonbank lender. For example, relative to white-owned restaurants, Black-owned restaurants are only 30% as likely to have a secured loan with a bank (6% vs. 20%). The means for the Yelp variables are fairly similar across demographic groups except for Black-owned restaurants, which have significantly fewer reviews, page views, and photos, although the average rating of Black-owned restaurants is similar to those of other groups. Like other demographic groups, almost all Black-owned restaurants accept credit cards.

¹² Gopal (2021) and Gopal and Schnabl (2020) also use UCC filings to measure lending to small businesses and provide more information on UCC filings.

¹³ <https://www.floridaucc.com/uccweb/ucc.aspx>

Table 2
Summary Statistics

This table reports summary statistics for Florida restaurants matched to voter registration data versus the full sample of restaurants matched to Florida corporate records. The sample consists of restaurants with seating that were licensed before February 15, 2020, whose license holders are Florida for-profit firms registered before February 15, 2020, whose owner’s race can be identified using Florida voter registration data, and that are matched to Yelp. Hotel and franchise restaurants are excluded.

	Final sample ($N = 9,980$)				Corporate records ($N = 21,761$)			
	Mean	SD	25th	75th	Mean	SD	25th	75th
Number of seats	87.97	103.44	35.00	135.00	86.94	101.16	30.00	130.00
Firm age	9.89	9.39	3.14	13.72	9.16	9.51	2.79	12.43
Bank UCC	0.16	0.37	0.00	0.00	0.15	0.36	0.00	0.00
Nonbank UCC	0.13	0.34	0.00	0.00	0.14	0.34	0.00	0.00
EIDL	0.36	0.48	0.00	1.00	0.33	0.47	0.00	1.00
PPP (2020)	0.70	0.46	0.00	1.00	0.66	0.48	0.00	1.00
Bank PPP (2020)	0.64	0.48	0.00	1.00	0.58	0.49	0.00	1.00
Nonbank PPP (2020)	0.07	0.25	0.00	0.00	0.07	0.26	0.00	0.00
PPP (2021)	0.47	0.50	0.00	1.00	0.44	0.50	0.00	1.00
Bank PPP (2021)	0.42	0.49	0.00	1.00	0.39	0.49	0.00	1.00
Nonbank PPP (2021)	0.05	0.21	0.00	0.00	0.05	0.22	0.00	0.00

Minority-owned restaurants tend to be located in ZIP codes with larger populations and lower white population share. Black-owned restaurants, for example, are located in ZIP codes in which white people account for 56% of the overall population. In contrast, white-owned restaurants are located in ZIP codes in which white people account for 81% of the overall population. Black-owned restaurants are also located in ZIP codes with about 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 their use of emergency loans. Out of white-owned restaurants, 74% received a PPP loan. Almost all of these were from a bank. A third of white-owned restaurants received an EIDL loan, with most recipients also receiving a PPP loan. Only 5% of white-owned restaurants received an EIDL loan without also receiving a PPP loan.

The picture is very different for Black-owned restaurants. Only 48% received a PPP loan. Conditional on receiving a PPP loan, 29% of PPP loans were from a nonbank. Three times as many Black- as white-owned restaurants received an EIDL loan without also receiving a PPP loan, and 36% of Black-owned restaurants received neither PPP nor EIDL loans.

For the other demographic groups we consider, the pattern of outcomes is generally in between those for white and Black restaurant owners. Other minority-owned restaurants are less likely to receive bank PPP loans, more likely to receive nonbank PPP loans, more likely to receive EIDL loans without also receiving PPP loans, and more likely to receive no emergency loans at all.

Table 3
Utilization of Emergency Loans by Different Groups

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

	Total	Race/Ethnicity				Gender	
		White	Black	Asian	Hispanic	Male	Female
<i>N</i>	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

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 A5 shows the robustness of our results to analyzing single-restaurant firms, which account for 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 received a PPP loan and zero otherwise. We include racial, Hispanic and female restaurant-owner dummies, while excluding white restaurant-owner dummies, so we are measuring the likelihood that minority- and female-owned restaurants get a PPP loan relative to restaurants owned by white males. As shown in the first column, which reports the results for the regression without any controls, Black-owned restaurants are 25.0% less likely than white-owned restaurants to receive a PPP loan, while Hispanic-owned restaurants are 9.1% less likely. Both coefficients are statistically significant. Asian-owned restaurants are 2.2% less likely to receive a PPP loan, although the difference is not statistically significant, while restaurants owned by women are 4.2% less likely to receive a PPP loan.

One reason why minority-owned restaurants may be less likely to receive PPP loans is that they are located in 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 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. Given that Black-owned restaurants are more likely to be in ZIP codes with low branch density, lower household income and more COVID cases per capita, the estimated magnitude of the disparity in PPP utilization 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 estimated disparities in PPP loans for Black-owned restaurants from 21.0% with controls to 19.8% with fixed effects. There is a similar modest impact on estimated disparities for Hispanic-owned restaurants, reducing the magnitude of the coefficient from 6.8% to 6.3%. Thus, a combination of bank branch density, household income,

Table 4
Racial Disparities in the Utilization of Emergency Loans

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

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

where f indexes firms, r indexes restaurants and z indexes ZIP codes. The sample consists of restaurants with seating that were licensed before February 15, 2020, whose license holders are Florida for-profit firms registered before February 15, 2020, whose owner's race can be identified using Florida voter registration data, and that are matched to Yelp. Hotel and franchise restaurants are excluded. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Except for the number of employees, 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*** (0.026)	-0.210*** (0.026)	-0.198*** (0.029)	-0.098*** (0.028)	-0.336*** (0.025)	-0.293*** (0.025)	-0.270*** (0.028)	-0.166*** (0.027)
Hispanic	-0.091*** (0.013)	-0.068*** (0.014)	-0.063*** (0.015)	-0.032** (0.015)	-0.099*** (0.013)	-0.074*** (0.014)	-0.068*** (0.016)	-0.035** (0.015)
Asian	-0.022 (0.015)	-0.018 (0.015)	-0.014 (0.016)	0.007 (0.016)	-0.103*** (0.016)	-0.098*** (0.016)	-0.092*** (0.017)	-0.067*** (0.017)
Other	-0.042* (0.024)	-0.032 (0.024)	-0.026 (0.025)	-0.011 (0.025)	-0.082*** (0.025)	-0.071*** (0.026)	-0.061** (0.026)	-0.043* (0.026)
Female	-0.042*** (0.010)	-0.038*** (0.010)	-0.030*** (0.011)	-0.007 (0.011)	-0.054*** (0.011)	-0.049*** (0.011)	-0.042*** (0.011)	-0.017 (0.011)
Bank branches per capita		0.025*** (0.005)				0.032*** (0.005)		
Ln(Population)		-0.007 (0.006)				-0.006 (0.006)		
Ln(Household income)		0.038*** (0.005)				0.039*** (0.005)		
COVID cases per capita		-0.013* (0.007)				-0.012 (0.008)		
Log(Number of seats)				0.049*** (0.005)				0.055*** (0.006)
Ln(Firm age)				0.036*** (0.005)				0.043*** (0.005)
Accepts credit cards				0.188*** (0.041)				0.161*** (0.041)
Missing credit cards				-0.012 (0.021)				-0.007 (0.021)
Ln(Reviews)				0.046*** (0.010)				0.046*** (0.010)
Average rating				-0.021** (0.010)				-0.015 (0.010)
No reviews				-0.154*** (0.044)				-0.119*** (0.045)
Ln(Page views)				0.001 (0.011)				-0.007 (0.012)
Ln(Photos)				0.040*** (0.007)				0.052*** (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*** (0.018)	0.083*** (0.018)	0.072*** (0.019)	0.067*** (0.019)	0.049* (0.025)	0.051** (0.026)	0.042 (0.029)	0.054* (0.029)
Hispanic	0.008 (0.006)	0.006 (0.007)	0.005 (0.008)	0.003 (0.008)	0.079*** (0.013)	0.065*** (0.014)	0.042*** (0.016)	0.042*** (0.016)
Asian	0.081*** (0.011)	0.081*** (0.011)	0.079*** (0.011)	0.074*** (0.011)	0.031* (0.016)	0.024 (0.016)	0.015 (0.017)	0.014 (0.018)
Other	0.040*** (0.015)	0.039*** (0.015)	0.035** (0.015)	0.032** (0.015)	0.062** (0.025)	0.059** (0.026)	0.048* (0.027)	0.047* (0.027)
Female	0.012** (0.006)	0.011* (0.006)	0.012** (0.006)	0.010* (0.006)	−0.020* (0.011)	−0.017 (0.011)	−0.007 (0.011)	−0.005 (0.011)
Bank branches per capita		−0.007*** (0.003)				0.021*** (0.006)		
Ln(Population)		−0.001 (0.003)				0.018*** (0.006)		
Ln(Household income)		−0.001 (0.003)				0.008 (0.005)		
COVID cases per capita		−0.001 (0.004)				0.026*** (0.007)		
Log(Number of seats)				−0.006* (0.003)				0.012** (0.006)
Ln(Firm age)				−0.008*** (0.003)				−0.014** (0.005)
Accepts credit cards				0.028 (0.017)				0.088** (0.038)
Missing credit cards				−0.005 (0.011)				−0.007 (0.022)
Ln(Reviews)				−0.000 (0.005)				0.013 (0.011)
Average rating				−0.007 (0.006)				0.032*** (0.010)
No reviews				−0.035 (0.024)				0.103** (0.045)
Ln(Page views)				0.008 (0.006)				0.003 (0.012)
Ln(Photos)				−0.012*** (0.004)				−0.005 (0.008)
R^2	0.015	0.015	0.107	0.109	0.004	0.008	0.097	0.100
ZIP FEs			✓	✓			✓	✓

and COVID cases per capita does a good job explaining variation in disparities across ZIP codes. Nevertheless, disparities for Black-owned restaurants remain large and statistically significant despite the inclusion of ZIP code fixed effects. The estimates for Hispanic-owned restaurants are smaller but still statistically significant.

We next consider whether restaurant characteristics affect the demand and supply of PPP loans. Thus, in column 4, we add controls for firm age and size, using the log number of restaurant seats as a proxy for size. We also add a variety of restaurant characteristics from Yelp, all measured pre-pandemic. Larger and older restaurants are significantly more likely to receive PPP loans, as are those that accept credit cards and have more Yelp customer reviews and posted photos. These variables presumably measure how well established and popular the restaurant was prior to the pandemic. There are two reasons to include these controls. The first is that these characteristics could help control for PPP loan demand if smaller, less established and less popular restaurants were less profitable and thus more likely to shut down during the pandemic and not apply for a PPP loan. The second is that these characteristics could control for loan supply as larger, more established and popular restaurants may have been prioritized by PPP lenders. This could be because they were more likely to be existing customers of the lender. It is also possible they were prioritized because there were more fees to be earned from making larger PPP loans or because these restaurants were more likely to ultimately survive and become future customers of the lender.

Importantly, controlling for 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, disparities that are still statistically significant. With the full set of controls there are no statistically significant disparities for Asian- and female-owned restaurants.

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

Columns 1–4 of Panel B in Table 4 tell a very different story for nonbank PPP loans. The regressions indicate that nonbanks tend to offset the lower rate of bank PPP lending to minority-owned restaurants, particularly in the case of restaurants with Black and Asian owners. The regression results reported in column 4, which include ZIP code fixed effects and restaurant characteristics,

indicate that Black-owned restaurants are 6.7% more likely to receive a nonbank PPP loan and Asian-owned restaurants are 7.4% more likely to receive a nonbank PPP loan. The higher take-up rate of nonbank PPP loans by Black- and Asian-owned restaurants suggests that these businesses substitute away from banks because they find it more difficult or less desirable to access PPP loans from banks. Note that the substitution to nonbank PPP loans is large enough for Asian-owned restaurants to fully offset their lower rate of borrowing from banks, but this is not the case for Black-owned restaurants, which have lower rates of overall PPP utilization. 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 utilization. As noted above, firms apply for EIDL loans directly through the SBA website. They can apply for and receive loans from both PPP and EIDL at the same time, though the proceeds must be used for different purposes. In the column 8 regression, which includes controls for location and restaurant characteristics, Black-owned restaurants are 5.4% more likely than white-owned restaurants to receive EIDL loans, though the difference is only statistically significant at the 10% level. Hispanic-owned restaurants are 4.2% more likely than white-owned restaurants to receive loans from EIDL, which is statistically significant.

The fact that minority-owned restaurants 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 ??, we more fully examine the possibility that our findings are explained by minority-owned restaurants having lower demand for emergency loans. For example, it is possible that that minority-owned restaurants 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 that were 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 in Section ?? that allow us to reject the hypothesis that disparities in PPP utilization stem from lower demand for PPP loans from minority-owned businesses.

Before moving on to an analysis of whether bank relationships and racial bias could help to explain racial disparities, we note that our findings are robust to a number of alternative sample specifications. In columns 1 and 4 of Appendix Table A5, we restrict the sample to single-restaurant firms, which account for 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

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

equal to one if either the firm itself or any of its affiliates receives a bank PPP loan. We consider two firms to be affiliated if they have the same first officer.¹⁵ We find somewhat stronger results when incorporating information about PPP loans received by affiliates. Finally, in columns 3 and 5 we examine robustness to using fixed effects for Census block groups, a much more granular geography than ZIP code. This regression is meant to address the concern that even within a ZIP code, minority-owned restaurants may be located farther away from bank branches or may be subject to different shocks. We obtain 2010 Census block information from the Census geocoder¹⁶ and Texas A&M GeoServices.¹⁷ 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. We find similar results when comparing minority- and white-owned restaurants within these more narrowly defined geographic areas.

4 Bank Relationships

In this section we explore the role that bank relationships could play in explaining racial disparities in PPP utilization. If banks prioritize businesses with which they have strong relationships, and minority-owned businesses have relatively weak relationships with banks, then we would expect to see racial disparities in bank PPP utilization without adequate controls for these relationships. Numerous studies have shown that Black- and Hispanic-owned businesses are more likely to be turned down for loans, controlling for credit quality and personal wealth, and less likely to apply for loans (Blanchflower, Levine, and Zimmerman, 2003; Cavalluzzo and Wolken, 2005; Fairlie, Robb, and Robinson, 2020). In addition, minority-owned businesses report greater dissatisfaction with their financial services providers (Federal Reserve Banks, 2021). This evidence suggests that, relative to white-owned restaurants, minority-owned restaurants have weaker relationships with banks.

While we do not observe the full extent of a restaurant’s banking relationships, it is likely that almost all of the restaurants in the sample have some kind of banking relationship 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 because they have been bank customers for a longer time. To get at the strength of a firm’s relationship with a bank, we collect data on whether a firm has a bank loan outstanding. Although we cannot observe all of a firm’s loans, we can observe secured loans except those that are secured by real estate. According to Luck and Santos (2021), out of all loans to firms with less than \$50 million in assets by banks that have been subject to the Federal Reserve’s stress tests, only 3.6% are unsecured

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

¹⁶ <https://geocoding.geo.census.gov/geocoder/>

¹⁷ <https://geoservices.tamu.edu>

and 22% are secured by real estate. Furthermore, [Blanchflower, Levine, and Zimmerman \(2003\)](#) show that Black-owned firms utilize credit cards as a form of debt at the same rate as white-owned firms. Thus, it is likely that by observing non-mortgage secured loans we are observing the most meaningful cross-sectional variation in a firm’s borrowing.

As noted in the data section, we use Florida Uniform Commercial Code (UCC) financing statements to measure secured borrowing relationships between restaurants and their lenders, both banks and nonbanks. These financing statements are filed by lenders to assert their security interest in a loan. The security interest could be in physical capital, such as equipment, or it could be a general lien on the business. We consider a restaurant to have a secured borrowing relationship with a lender if there was an active UCC filing by that lender as of February 15, 2020. As shown in [Table 3](#), the percentage of minority-owned restaurants that have UCC loans with banks is considerably lower than it is for white-owned restaurants, although the percentages are quite similar for loans from nonbanks. In particular, only 6% of Black-owned restaurants have outstanding UCC loans from banks, while 20% of white-owned restaurants have such loans.

The dependent variable in the first three columns of [Table 5](#) Panel A is whether the restaurant receives a PPP loan. In columns 4–6 we present regression results for bank PPP loans. In Panel B of the table we present results for nonbank PPP loans (columns 1–3) and EIDL loans (columns 4–6). The first column in each block of regressions (PPP, bank PPP, nonbank PPP, EIDL) repeats the baseline specifications from columns 4 and 8 of both panels in [Table 4](#). The other columns add controls for whether the firm has an active bank or nonbank UCC loan and interaction terms described below. All regressions include ZIP code fixed effects and the full set of restaurant characteristics from [Table 4](#), although they are not shown.

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

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

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 a very modest effect on the coefficients of the minority-owned restaurant dummies and almost no effect on the Black-owned

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. 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%. Except for the number of employees, 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*** (0.028)	-0.099*** (0.028)	-0.070** (0.031)	-0.166*** (0.027)	-0.164*** (0.027)	-0.144*** (0.029)
Hispanic	-0.032** (0.015)	-0.030** (0.015)	-0.029* (0.017)	-0.035** (0.015)	-0.032** (0.015)	-0.032* (0.017)
Asian	0.007 (0.016)	0.014 (0.016)	0.013 (0.017)	-0.067*** (0.017)	-0.059*** (0.017)	-0.063*** (0.019)
Other	-0.011 (0.025)	-0.007 (0.025)	0.011 (0.028)	-0.043* (0.026)	-0.040 (0.026)	-0.025 (0.029)
Female	-0.007 (0.011)	-0.005 (0.011)	-0.008 (0.012)	-0.017 (0.011)	-0.015 (0.011)	-0.012 (0.012)
Bank UCC loan		0.053*** (0.012)	0.072*** (0.019)		0.077*** (0.013)	0.101*** (0.021)
Nonbank UCC loan		0.054*** (0.012)	0.077*** (0.017)		0.024* (0.014)	0.034* (0.019)
Black \times Bank UCC loan			-0.182* (0.100)			-0.253** (0.099)
Black \times Nonbank UCC loan			-0.097 (0.076)			0.015 (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
Panel B: Nonbank PPP and EIDL						
	Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.067*** (0.019)	0.065*** (0.019)	0.075*** (0.021)	0.054* (0.029)	0.050* (0.029)	0.049 (0.031)
Hispanic	0.003 (0.008)	0.002 (0.008)	0.003 (0.008)	0.042*** (0.016)	0.043*** (0.016)	0.041** (0.017)
Asian	0.074*** (0.011)	0.074*** (0.011)	0.076*** (0.012)	0.014 (0.018)	0.023 (0.018)	0.013 (0.019)
Other	0.032** (0.015)	0.033** (0.015)	0.036** (0.017)	0.047* (0.027)	0.052* (0.027)	0.055* (0.030)
Female	0.010* (0.006)	0.010 (0.006)	0.005 (0.007)	-0.005 (0.011)	-0.002 (0.011)	0.003 (0.013)
Bank UCC loan		-0.024*** (0.006)	-0.029*** (0.010)		0.054*** (0.014)	0.091*** (0.025)
Nonbank UCC loan		0.030*** (0.008)	0.043*** (0.012)		0.108*** (0.015)	0.139*** (0.022)
Black \times Bank UCC loan			0.071 (0.076)			0.171 (0.122)
Black \times Nonbank UCC loan			-0.112** (0.046)			-0.079 (0.083)
UCC bank's PPP intensity			-0.002 (0.003)			-0.023*** (0.008)
R^2	0.109	0.112	0.115	0.100	0.107	0.111
ZIP FEs	✓	✓	✓	✓	✓	✓
Controls		✓	✓		✓	✓
Controls \times UCC			✓			✓

restaurant dummy.

Why doesn't controlling for secured borrowing relationships have a bigger effect on estimated disparities? We would expect a larger 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.¹⁸ However, this assumes that bank borrowing relationships have the same effect on PPP access for white-owned and minority-owned restaurants. One potential reason why the effects could be different is that minority-owned restaurants may have relationships with banks that were less active PPP lenders, and thus had to find other banks from which to receive PPP loans. To examine this possibility, we look at 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 to 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 for why controlling for borrowing relationships has a limited effect 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 bank PPP loan.

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 Appendix Table A6. 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 bank PPP utilization. In the bank PPP regression shown in column 6, the estimated coefficients of the bank UCC loan variable interacted 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

¹⁸ 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 utilization by Hispanic-owned restaurants to fall by 0.77%; in fact, it falls by only 0.20%.

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, what we can conclude is that bank borrowing relationships are less valuable for Black-owned restaurants than they are for white-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 the bank for a PPP loan.

Importantly, the coefficients of the minority restaurant-owner dummies in the regression in column 6 also tells us that disparities in bank PPP utilization 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 prior bank relationship predicts an increased likelihood of getting a bank PPP loan, it is not surprising that it reduces the probability of getting a nonbank PPP loan. The fact that restaurants with prior nonbank loans are more likely to receive nonbank PPP loans suggests that these nonbank relationships also confer advantages in receiving PPP loans. The coefficients of the interaction terms are reported in column 3. While not statistically significant, the positive coefficient on the bank UCC loan variable indicates that Black-owned restaurants with these outstanding loans are more likely to apply for nonbank PPP loans, consistent with the finding that they are less likely to receive bank PPP loans. These results also indicate that Black-owned restaurants with nonbank UCC loans are less likely to apply for nonbank PPP loans suggesting that nonbank borrowing relationships, like bank borrowing relationships, confer less advantage to Black-owned restaurants. It is also possible that compared to white-owned businesses that receive nonbank UCC loans, Black-owned businesses are less likely to receive nonbank UCC loans from lenders that participate in the PPP program. For example, Black-owned businesses may be more likely to borrow from equipment finance companies or merchant cash advance lenders, which are presumably less likely to participate in PPP relative to fintech lenders.

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

5 Racial Bias

In this section, we look at the effect of racial bias on bank PPP utilization. Specifically, we ask whether minority-owned restaurants are less likely to receive PPP loans in locations with more racial bias among the white population. We use data on explicit and implicit racial bias collected by Project Implicit.¹⁹ Project Implicit offers a number of online implicit association tests that test-takers anywhere in the world can take to measure their implicit social attitudes. We use the results of the Race test, also known as the Black/White test, which measures implicit preference for white over Black people.²⁰ The test also asks subjects about their explicit preferences on a seven-point scale, where 1 is “I strongly prefer African Americans to European Americans”, 4 is “I like European Americans and African Americans equally”, and 7 is “I strongly prefer European Americans to African Americans.”

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

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

Table 6 reports the results of linear probability models for PPP loans and bank PPP loans in

¹⁹ <https://osf.io/y9hiq/>

²⁰ 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.

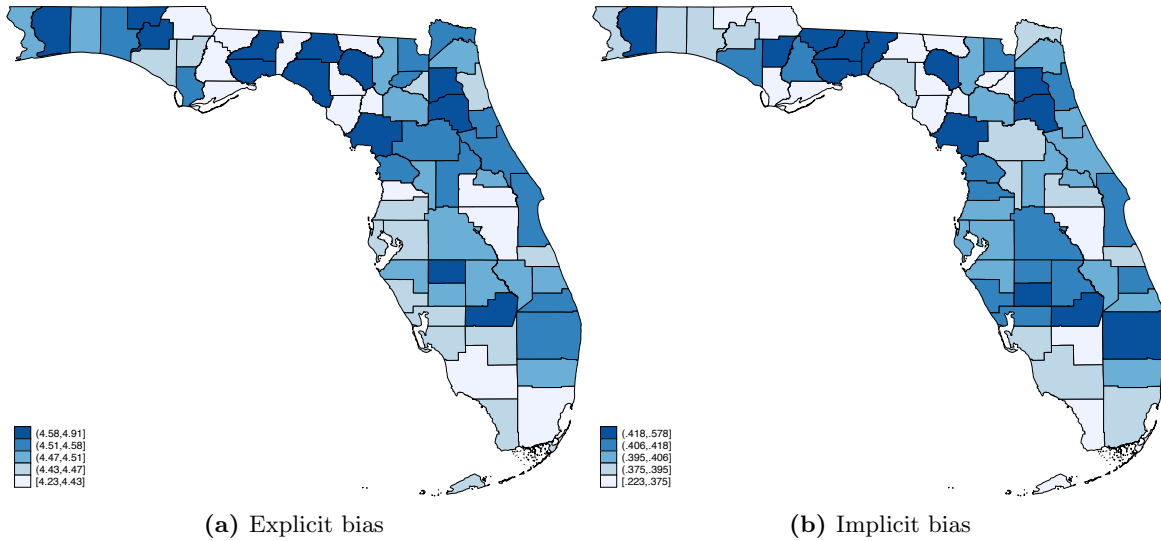


Figure 1. Explicit and implicit racial bias across Florida counties This figure reports county-level averages of explicit and implicit racial bias of white respondents to the [Race Implicit Association Test](#). Larger values indicate stronger bias against African Americans. Explicit bias is measured 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.

Panel A, and nonbank PPP loans and EIDL loans in Panel B. The main variables of interest are the minority restaurant-owner dummies and their interactions with county-level explicit and implicit bias. Odd-numbered columns report the results for explicit bias, while even-numbered columns report the results for implicit bias. County-level bias measures are standardized to a mean of zero and unit standard deviation so that the interaction coefficients capture the effect of a one standard deviation increase in racial bias. The direct effect of bias in a county is absorbed by the ZIP code fixed effects included throughout. To account for the likelihood that bias in counties with few test takers is measured with more noise, observations are weighted by the number of responses in the county. Equal weighted regressions generate slightly weaker results. Standard errors are adjusted for clustering by county to match the level at which we measure the key explanatory variable. All regressions include restaurant characteristics and UCC loans although their estimated coefficients are not reported.

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

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. 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%. Except for the number of employees, 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 (0.065)	−0.119** (0.046)	−0.223*** (0.038)	−0.168*** (0.024)	0.118*** (0.037)	0.049 (0.034)	0.061 (0.043)	0.018 (0.034)
Hispanic	−0.056** (0.022)	−0.034** (0.015)	−0.038 (0.024)	−0.022 (0.019)	−0.017*** (0.006)	−0.012** (0.006)	0.063** (0.031)	0.062*** (0.017)
Asian	0.008 (0.020)	0.003 (0.012)	−0.081*** (0.027)	−0.055*** (0.021)	0.090*** (0.013)	0.058*** (0.011)	0.013 (0.030)	0.003 (0.036)
Other	−0.083*** (0.029)	0.002 (0.023)	−0.093*** (0.030)	−0.033 (0.027)	0.010 (0.016)	0.035 (0.023)	0.051* (0.029)	0.052** (0.022)
Female	−0.008 (0.008)	−0.010 (0.008)	−0.035*** (0.010)	−0.026*** (0.007)	0.027** (0.011)	0.017** (0.008)	−0.009 (0.016)	−0.003 (0.011)
Black × Bias	0.030 (0.131)	0.062 (0.106)	−0.139* (0.070)	−0.151** (0.063)	0.169** (0.075)	0.213** (0.091)	0.099 (0.098)	0.175* (0.099)
Hispanic × Bias	−0.056 (0.052)	−0.088 (0.056)	−0.045 (0.062)	−0.079 (0.069)	−0.011 (0.014)	−0.009 (0.016)	0.006 (0.038)	0.024 (0.037)
Asian × Bias	0.012 (0.033)	0.051 (0.044)	−0.064 (0.057)	−0.046 (0.091)	0.076** (0.031)	0.097* (0.049)	0.023 (0.085)	0.021 (0.100)
Other × Bias	−0.213*** (0.054)	−0.253*** (0.086)	−0.147 (0.089)	−0.215** (0.097)	−0.066 (0.060)	−0.038 (0.082)	−0.004 (0.050)	0.015 (0.086)
Female × Bias	0.004 (0.016)	0.003 (0.018)	−0.021 (0.013)	−0.025** (0.012)	0.024* (0.014)	0.028 (0.018)	−0.015 (0.023)	−0.032 (0.023)
R^2	0.170	0.170	0.180	0.180	0.103	0.103	0.097	0.097
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓

bank PPP loan. In both regressions, the interaction between *Bias* and *Black* is negative and statistically significant. The magnitude of the effect is very large. A one standard deviation increase in racial bias is associated with 13.9%–15.1% reduction in the probability that a Black-owned restaurant receives a bank PPP loan, depending on whether we use explicit or implicit bias as the measure. Given that Black-owned restaurants are 22.3% (16.8%) less likely get a bank PPP loan in a county with average explicit (implicit) bias, this implies that Black-owned restaurants are 36.2% (31.9%) less likely to receive bank PPP funding in counties with explicit (implicit) bias one standard deviation above the mean.²¹ The interactions between racial bias and the other minority restaurant-owner dummies are also negative, but smaller in magnitude and generally not

²¹ 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.

statistically significant. It makes sense that although bias towards Black people may be correlated with bias against other minority groups, its strongest effect is on the likelihood that Black-owned restaurants receive bank PPP loans.

In columns 5 and 6, we present results for nonbank PPP loans. Here the coefficient on the interaction between *Black* and *Bias* is 16.9%–21.3% and statistically significant, the opposite of the sign for bank PPP loans. These results suggest that Black-owned restaurants are more likely to substitute from bank to nonbank PPP loans in counties with greater racial bias. In fact, the extent of substitution is so strong in more racially biased counties that it fully offsets the lower levels of bank PPP utilization in these counties, which is why the interaction terms in columns 1 and 2 are essentially zero. Note, however, that in the average county there are still disparities between Black- and white-owned restaurants in access to PPP.

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

One may be concerned that racial bias is correlated with other county-level characteristics in a way that may explain differences in take-up rates and drive the results in Table 6. Table A3 in the 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.

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

Finally, we study whether racial disparities were attenuated in the third round of PPP, which began on January 11, 2021. To improve access to the program by small and minority-owned businesses, the Small Business Administration instituted a number of changes to the program in this round. These include setting aside funds for the following: lending by Community Financial Institutions (CFIs) and by banks with less than \$10 billion in assets; lending to new PPP borrowers; lending to small firms with at most 10 employees; and lending less than \$250,000 to borrowers in low- or moderate-income neighborhoods. The SBA also provided a window of exclusive access to the program by CFIs with less than \$1 billion in assets. In total, \$278 billion of loans were made in the third round of PPP. We explore whether the changes made in this round mitigated racial disparities in the program.

The results in Table 7, which use data running from January 12 through June 30, 2021, suggest that there was some attenuation in racial disparities in the case of Black-owned restaurants, particularly in more racially biased counties. Columns 1–2 report the results for PPP utilization, columns 3–4 report the results for bank PPP utilization, 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 7 and Table 6, both of which use 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 disparities 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 in these more racially biased counties Black-owned restaurants are more likely to receive PPP loans. This may be because these were the counties in which Black-owned restaurants owners had more pent-up demand for PPP loans given their lower take-up rates in the first two rounds. This pent-up demand could be satisfied because of the measures taken in the third round to enhance access to underserved businesses.

6 Alternative Explanations

As previously noted in Section 3 above, an alternative explanation of our core finding of disparities in PPP utilization 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 bank PPP utilization by Black-owned restaurants in more racially biased counties, combined with the greater substitution to nonbank loans and EIDL loans in those counties. Nevertheless, to further and more directly ad-

Table 7
Round 3 of PPP

This table reports the results of linear probability model regressions of the utilization of PPP loans during the third round of the program from January 12 through April 30, 2021. Controls include all restaurant characteristics included in the regression in column 2 of Table 5. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Except for the number of employees, 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 (0.048)	-0.078*** (0.026)	-0.063* (0.037)	-0.096*** (0.017)	0.050** (0.019)	0.018 (0.015)
Hispanic	-0.039* (0.021)	-0.022 (0.015)	-0.052*** (0.017)	-0.022 (0.016)	0.013 (0.014)	-0.000 (0.009)
Asian	0.018 (0.022)	-0.001 (0.012)	-0.032 (0.024)	-0.040*** (0.012)	0.050*** (0.018)	0.039*** (0.012)
Other	-0.008 (0.037)	-0.033 (0.029)	-0.055*** (0.020)	-0.079*** (0.016)	0.047* (0.027)	0.046** (0.021)
Female	-0.011 (0.016)	-0.020 (0.013)	-0.032** (0.014)	-0.034*** (0.012)	0.022*** (0.006)	0.014*** (0.002)
Black \times Bias	0.154** (0.072)	0.226*** (0.039)	0.074 (0.064)	0.133*** (0.043)	0.079*** (0.021)	0.094*** (0.024)
Hispanic \times Bias	-0.038 (0.056)	-0.036 (0.061)	-0.070 (0.051)	-0.076 (0.060)	0.032* (0.018)	0.040 (0.028)
Asian \times Bias	0.045 (0.040)	0.070** (0.032)	0.018 (0.040)	0.056 (0.042)	0.027 (0.021)	0.014 (0.027)
Other \times Bias	0.063 (0.073)	0.045 (0.091)	0.060* (0.035)	0.045 (0.030)	0.002 (0.054)	0.000 (0.068)
Female \times Bias	0.023 (0.021)	0.049** (0.021)	0.005 (0.020)	0.016 (0.021)	0.019* (0.010)	0.033*** (0.012)
R^2	0.161	0.161	0.164	0.164	0.091	0.090
ZIP FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

dress any remaining concerns, this section explores whether minority-owned restaurants have lower demand for emergency loans. We first examine whether there were observable differences between minority- and white-owned restaurants during the pandemic that 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 Controlling for 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, it is possible that minority-owned restaurants were more likely to shut down during the pandemic or operated 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 that were 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 a number of measures of restaurant activity during the pandemic to see whether it could help explain the estimated racial disparities. Note that while activity levels may explain PPP utilization, it is also possible that PPP utilization could help to explain activity levels, as the take-up of a PPP loan could help a restaurant stay in business. Thus, including pandemic activity levels could lead us to underestimate racial disparities in PPP utilization.

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 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, which 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. Importantly, while this finding indicates that more active restaurants are indeed 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, which collects anonymous data on visits to different points of interest using cell phone tracking.²² 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.

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 have a material effect on estimated racial disparities.

²² 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
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. 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(Monthly visits during pandemic) is the natural log of one plus the average number of monthly visits during March–July 2020. Monthly visits are from SafeGraph. Ln(Monthly visits before pandemic) is the natural log of one plus the average number of monthly visits during October 2019–February 2020. 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%. Except for the number of employees, 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*** (0.029)	−0.100*** (0.029)	−0.114*** (0.030)	−0.126*** (0.033)	−0.171*** (0.028)	−0.169*** (0.028)	−0.177*** (0.029)	−0.174*** (0.033)
Hispanic	−0.031** (0.015)	−0.029* (0.015)	−0.031** (0.015)	−0.028* (0.016)	−0.032** (0.015)	−0.030* (0.016)	−0.030* (0.016)	−0.029* (0.017)
Asian	0.011 (0.016)	0.016 (0.016)	0.013 (0.016)	0.012 (0.017)	−0.063*** (0.017)	−0.056*** (0.018)	−0.060*** (0.018)	−0.066*** (0.019)
Other	−0.005 (0.025)	−0.002 (0.026)	−0.001 (0.026)	−0.012 (0.026)	−0.035 (0.026)	−0.027 (0.026)	−0.024 (0.026)	−0.044 (0.027)
Female	−0.005 (0.011)	−0.007 (0.011)	−0.008 (0.011)	−0.009 (0.011)	−0.016 (0.011)	−0.020* (0.011)	−0.022* (0.012)	−0.025** (0.012)
Ln(Reviews during pandemic)	0.013* (0.008)		0.009 (0.008)	0.006 (0.009)	0.027*** (0.008)		0.022*** (0.008)	0.020** (0.009)
Ln(Monthly visits during pandemic)		0.035** (0.015)	0.001 (0.016)	−0.006 (0.018)		0.032** (0.015)	0.001 (0.016)	−0.005 (0.019)
Ln(Monthly visits before pandemic)		−0.025* (0.015)	0.006 (0.016)	0.014 (0.018)		−0.021 (0.015)	0.007 (0.016)	0.013 (0.018)
<i>N</i>	9,736	9,297	9,082	8,213	9,736	9,297	9,082	8,213
<i>R</i> ²	0.180	0.185	0.183	0.181	0.192	0.198	0.195	0.191
Panel B: Nonbank PPP and EIDL								
	Nonbank PPP				EIDL			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	0.057*** (0.020)	0.069*** (0.021)	0.063*** (0.021)	0.049** (0.022)	0.045 (0.030)	0.043 (0.031)	0.034 (0.032)	0.043 (0.035)
Hispanic	0.000 (0.008)	0.001 (0.008)	−0.001 (0.008)	0.001 (0.009)	0.040** (0.016)	0.039** (0.016)	0.035** (0.017)	0.035** (0.018)
Asian	0.073*** (0.011)	0.073*** (0.012)	0.072*** (0.012)	0.078*** (0.013)	0.018 (0.018)	0.026 (0.018)	0.022 (0.018)	0.015 (0.020)
Other	0.030** (0.015)	0.026* (0.015)	0.023 (0.015)	0.032** (0.016)	0.046* (0.027)	0.056** (0.027)	0.049* (0.027)	0.036 (0.028)
Female	0.011* (0.006)	0.013** (0.006)	0.014** (0.006)	0.016** (0.007)	−0.006 (0.011)	−0.008 (0.012)	−0.012 (0.012)	−0.018 (0.013)
Ln(Reviews during pandemic)	−0.014*** (0.004)		−0.013*** (0.004)	−0.014*** (0.005)	−0.036*** (0.008)		−0.033*** (0.009)	−0.039*** (0.010)
Ln(Monthly visits during pandemic)		0.004 (0.007)	−0.000 (0.008)	−0.001 (0.009)		−0.019 (0.016)	−0.030* (0.018)	−0.048** (0.019)
Ln(Monthly visits before pandemic)		−0.004 (0.007)	−0.000 (0.008)	0.001 (0.008)		0.012 (0.016)	0.022 (0.017)	0.037** (0.019)
<i>N</i>	9,736	9,297	9,082	8,213	9,736	9,297	9,082	8,213
<i>R</i> ²	0.115	0.116	0.119	0.128	0.113	0.116	0.121	0.131
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Exclude closed restaurants				✓				✓

6.2 Unobservable Differences in Demand for PPP Loans

Although our regression specifications control for an extensive set of observable restaurant characteristics—both before the pandemic and during the pandemic—it is possible that there are unobservable differences in demand that could help to explain racial disparities in the take-up of PPP loans. 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 for why they did not apply; only 7% of white-owned non-applicants cited this reason (Federal Reserve Banks, 2021). Another possibility is that, even controlling for location and restaurant activity, minority-owned restaurants may have fewer employees. Since the size of PPP loans is based on payroll, restaurants with fewer employees would 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.²³ The EIDL Advance program provided grants of \$1,000 per employee for 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. Thus we see that 80% of firms that received an EIDL Advance grant also applied for and received a PPP loan.²⁴ We can therefore ask whether there are racial disparities in the take-up of PPP loans among restaurants that received EIDL Advance grants.

Restricting the sample to EIDL Advance recipients has the added benefit of allowing us to control for the number of employees. Because the size of the grant is \$1,000 times the number of employees up to \$10,000, we can back out the number of employees up to 10. While we cannot back out the payroll, the number of employees should be closely correlated with payroll given our focus on restaurants and the similarity of the jobs within a restaurant. Because EIDL Advance grants are capped at \$10,000, we include a dummy variable for firms with at least ten employees. Alternatively, 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

²³ <https://data.sba.gov/dataset/covid-19-eidl-advance>.

²⁴ An EIDL Advance grant would count against the forgivable portion of the PPP loan.

Table 9
Take-Up of PPP 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. 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*** (0.040)	-0.137** (0.058)	-0.257*** (0.039)	-0.216*** (0.055)	0.093*** (0.031)	0.079* (0.042)
Hispanic	-0.038** (0.018)	-0.040 (0.037)	-0.019 (0.020)	-0.049 (0.038)	-0.019* (0.011)	0.009 (0.021)
Asian	0.018 (0.019)	0.034 (0.033)	-0.060*** (0.022)	-0.063* (0.036)	0.078*** (0.016)	0.097*** (0.024)
Other	-0.023 (0.030)	-0.049 (0.055)	-0.068** (0.032)	-0.119** (0.055)	0.046* (0.024)	0.070* (0.040)
Female	-0.011 (0.014)	-0.006 (0.025)	-0.027* (0.015)	-0.035 (0.027)	0.017* (0.010)	0.029* (0.017)
Num. employees	0.054*** (0.004)	0.051*** (0.005)	0.055*** (0.005)	0.052*** (0.006)	-0.001 (0.003)	-0.001 (0.004)
I(Num. employees \geq 10)	-0.097*** (0.025)		-0.098*** (0.027)		0.001 (0.017)	
<i>N</i>	4,935	2,141	4,935	2,141	4,935	2,141
<i>R</i> ²	0.320	0.388	0.323	0.381	0.193	0.314
ZIP FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Exclude firms with \geq 10 employees		✓		✓		✓

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 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. Importantly, the disparities in PPP utilization 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 take-up rate of PPP loans 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 utilization 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.

The finding that racial disparities in PPP exist within the subsample of restaurants that receive EIDL Advance grants indicates that racial disparities in PPP cannot be explained by lower demand for emergency support by minority-owned businesses or by less awareness of such support programs. Another way to establish that differences in demand for government support programs or awareness

of them cannot explain racial disparities in PPP 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 utilization 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 utilization within this subsample of firms, with Black- and Hispanic-owned restaurants both being significantly less likely to receive PPP loans. As before, the disparities are driven by disparities in bank lending. Banks are less likely to lend to minority-owned restaurants 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 provides further support for the view that unobserved differences across groups in emergency loan demand or loan awareness do not explain disparities in PPP lending.

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:

$$PPP_{f,r,z} = \alpha_z + \beta \cdot \text{Minority}_f + \delta \cdot \text{Female}_f + \gamma' X_{f,r} + \varepsilon_{f,r,z},$$

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%. Except for the number of employees, 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*** (0.027)	-0.145*** (0.030)	-0.101*** (0.029)	-0.330*** (0.032)	-0.275*** (0.035)	-0.213*** (0.034)
Hispanic	-0.074*** (0.010)	-0.058*** (0.011)	-0.050*** (0.011)	-0.088*** (0.012)	-0.067*** (0.014)	-0.052*** (0.014)
Asian	-0.014 (0.010)	-0.010 (0.011)	-0.001 (0.011)	-0.120*** (0.016)	-0.114*** (0.017)	-0.094*** (0.017)
Other	-0.047*** (0.018)	-0.036* (0.019)	-0.026 (0.019)	-0.099*** (0.024)	-0.083*** (0.025)	-0.068*** (0.024)
Female	-0.023*** (0.008)	-0.023*** (0.008)	-0.010 (0.008)	-0.041*** (0.010)	-0.039*** (0.011)	-0.022** (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 there is something special about restaurants given that restaurants were hit especially hard by the pandemic, and thus whether the results apply to other industries. Since we cannot identify the population of potential borrowers in other industries, we restrict our analysis to those firms receiving some form of government support, just as we did in the robustness

section above. First, we examine whether there are racial disparities in PPP 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, as well as variation in the use of emergency loans across industries, we control for industry in our analysis. While PPP data include NAICS industry classification, this information is not available in the EIDL data. To control for industry, we match PPP, 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 are able to match about two-thirds of PPP and EIDL borrowers to the Dun & Bradstreet database.

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

Panel A of Table 11 repeats the analysis in Table 9 for a broad set of industries, exploring whether minority-owned restaurants 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 minority-owned restaurant variables without 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 the utilization of PPP loans. The number of employees is positively related to the likelihood of receiving PPP loans. 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 11

Take-Up of PPP Loans Conditional on Receiving EIDL Advance

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%. Except for the number of employees, 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*** (0.007)	-0.128*** (0.021)	-0.091*** (0.018)	-0.081*** (0.020)	-0.247*** (0.007)	-0.178*** (0.011)	-0.139*** (0.011)	-0.121*** (0.012)
Hispanic	-0.146*** (0.005)	-0.101*** (0.012)	-0.071*** (0.011)	-0.071*** (0.013)	-0.144*** (0.008)	-0.095*** (0.011)	-0.066*** (0.010)	-0.065*** (0.011)
Asian	0.045*** (0.010)	0.009 (0.017)	0.005 (0.016)	-0.004 (0.020)	0.018* (0.010)	-0.015 (0.017)	-0.017 (0.016)	-0.022 (0.020)
Other	-0.057*** (0.015)	-0.055*** (0.014)	-0.033*** (0.011)	-0.033** (0.015)	-0.067*** (0.015)	-0.066*** (0.013)	-0.043*** (0.011)	-0.042** (0.017)
Female	-0.011*** (0.004)	-0.020*** (0.006)	0.005 (0.006)	0.006 (0.007)	-0.012*** (0.004)	-0.018*** (0.007)	0.006 (0.006)	0.007 (0.007)
Ln(Firm age)			0.044*** (0.005)	0.042*** (0.004)			0.043*** (0.005)	0.041*** (0.005)
Ln(Sales)			0.053*** (0.006)	0.056*** (0.007)			0.055*** (0.005)	0.056*** (0.007)
Num. employees			0.061*** (0.004)	0.061*** (0.004)			0.057*** (0.003)	0.057*** (0.004)
I(Num. employees ≥ 10)			-0.188*** (0.015)				-0.164*** (0.018)	
Bank UCC loan			0.088*** (0.014)	0.083*** (0.013)			0.107*** (0.012)	0.094*** (0.012)
Nonbank UCC loan			0.061*** (0.013)	0.061*** (0.015)			0.028** (0.013)	0.025 (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 ≥ 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*** (0.019)	-0.073*** (0.020)	-0.075*** (0.022)	-0.058*** (0.020)	-0.135*** (0.011)	-0.117*** (0.010)	-0.128*** (0.016)	-0.106*** (0.014)
Black \times Bias	-0.056 (0.045)	-0.079 (0.052)	-0.064 (0.044)	-0.112*** (0.040)	-0.066** (0.032)	-0.076** (0.033)	-0.063 (0.051)	-0.090** (0.041)
R^2	1	1	1	1	1	1	1	1
SIC-ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Exclude firms with ≥ 10 employees		✓		✓		✓		✓

Table 12
External Validity: PPP vs. EIDL

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%. Except for the number of employees, 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*** (0.006)	-0.229*** (0.011)	-0.210*** (0.017)	-0.153*** (0.019)	-0.389*** (0.011)	-0.313*** (0.008)	-0.294*** (0.014)	-0.228*** (0.015)
Hispanic	-0.235*** (0.006)	-0.167*** (0.007)	-0.159*** (0.014)	-0.122*** (0.013)	-0.241*** (0.009)	-0.172*** (0.009)	-0.161*** (0.015)	-0.120*** (0.014)
Asian	-0.023** (0.010)	-0.027*** (0.008)	-0.030*** (0.011)	-0.005 (0.011)	-0.056*** (0.011)	-0.056*** (0.009)	-0.063*** (0.012)	-0.034*** (0.011)
Other	-0.108*** (0.016)	-0.088*** (0.010)	-0.091*** (0.014)	-0.064*** (0.013)	-0.128*** (0.018)	-0.102*** (0.011)	-0.113*** (0.019)	-0.081*** (0.018)
Female	-0.019*** (0.003)	-0.016*** (0.002)	-0.017*** (0.006)	-0.003 (0.006)	-0.027*** (0.003)	-0.021*** (0.002)	-0.022*** (0.004)	-0.006 (0.005)
Ln(Firm age)				0.062*** (0.004)				0.069*** (0.004)
Ln(Sales)				0.056*** (0.006)				0.056*** (0.006)
Ln(Employees)				-0.004 (0.003)				0.006* (0.003)
Bank UCC loan				0.076*** (0.006)				0.106*** (0.007)
Nonbank UCC loan				0.059*** (0.008)				0.028*** (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*** (0.020)	-0.138*** (0.020)	-0.132*** (0.025)	-0.132*** (0.023)	-0.217*** (0.017)	-0.217*** (0.017)	-0.203*** (0.026)	-0.202*** (0.023)
Black × Bias	-0.066 (0.054)	-0.067 (0.045)	-0.057 (0.063)	-0.057 (0.051)	-0.114** (0.056)	-0.116*** (0.035)	-0.117 (0.074)	-0.119** (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 dummies × Bias	✓		✓		✓		✓	

Table 12 examines whether there are disparities in PPP utilization and bank PPP utilization conditional on receiving either PPP or EIDL loans. The first column in each block of regressions estimates minority-owned restaurant variables without controls for location, industry and firm characteristics. The second column in each block adds ZIP code and industry fixed effects, while

the the third column adds industry cross ZIP code fixed effects. Finally, the fourth column in each block adds log firm age, log sales and log number of employees (from D&B), as well as prior bank and nonbank UCC loans. These variables tell a familiar story: larger and older firms with a history of bank and nonbank borrowing are more likely to receive PPP loans from banks. As in the baseline regressions, adding controls reduces estimated disparities for both PPP and bank PPP loans, but these disparities remain large and statistically significant for Black- and Hispanic-owned firms. Even with controls, Black-owned businesses are 15.3% less likely to receive PPP loans and 22.8% less likely to receive bank PPP loans. Hispanic-owned businesses are also 12.2% less likely to receive PPP loans, and 12.0% less likely to receive them from banks.

Table 12, Panel B examines whether disparities are 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 of the regressions include ZIP code cross industry fixed effects and the same controls as in Table 12. 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.

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 utilization.

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

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

were much less likely to have a bank borrowing relationship in the first place.

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

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

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

Linking approved PPP loans to Florida corporate records

1. We start with the sample of borrower who according to PPP data are located in Florida. Some of these will turn out to be firms registered in other states and will be dropped after linking to Florida corporate records.
2. Because our focus is on for profit incorporated businesses, we drop non-profits, cooperatives, employee stock ownership plans (ESOPs), joint ventures, partnerships, professional associations, and a few other rare business types. Business types remaining in the sample are
 - Corporation
 - Independent Contractors
 - Limited Liability Company (LLC)
 - Limited Liability Partnership
 - Self-Employed Individuals
 - Sole Proprietorship
 - Subchapter S Corporation

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

3. Match exactly on firm name after removing punctuation and standardizing legal form (for example replacing "Corporation" with "Corp").
4. Match exactly on firm name after removing white space.
5. Match after removing legal form.
6. Set aside borrowers that have not been matched up to this point and that can be matched to Florida voter registration or white pages data. We parse borrower name into first and last names, and try to match these to voter registration data. If there is at least one match in voter registration data, we tag borrower as an individual.
7. Fuzzy match based on borrower name, ZIP, and street address. We require an exact match on ZIP and first five letters of firm name.

Linking restaurants to corporate records

1. Match restaurant license holder name to firm name in corporate records after removing punctuation and standardizing legal form. To break ties between multiple potential matches, we use the following screens.
 - (a) If there is a match that is currently active according to corporate records, drop inactive matches.
 - (b) If there is a match that has the same ZIP code, drop firms that do not match on ZIP code. We compare the principal address in corporate records with the restaurant location and the mailing address in corporate records with the license holder mailing address.
 - (c) If there is a match with the same city name, drop firms that do not match on city name.
 - (d) Keep only those licenses that match to a single corporate record. Three quarters of all restaurants are matched in this step.
2. Remove white space from license holder and firm names and repeat step 1 on unmatched restaurants.
3. Remove legal form from license holder and firm names and repeat step 1 on unmatched restaurants.
4. Try matching restaurant name to firm name in corporate records after removing punctuation and legal form. Apply the same procedure for breaking ties as in step 1.
5. Fuzzy match between license holder name and firm name.
 - (a) Match on ZIP code and first three letters of license holder and firm names.
 - (b) Calculate similarity score between license holder and firm names. We use bigram string matching method and calculate the Jaccard score. Specifically we split each name into bigrams, i.e., all possible sequences of two letters. The similarity score between two strings is then $\frac{m}{\sqrt{s_1 \times s_2}}$, where m is the number of bigrams the two strings have in common, and s_1 and s_2 are the numbers of bigram in the two strings.
 - (c) Consider the firm with the highest similarity score to be a match if the similarity score is greater than 0.80 and the difference compared to the next highest similarity score is at least 0.10.
6. Repeat step 5 but matching on city instead of ZIP code.
7. Fuzzy match between license holder name and first officer name in corporate records. Because a first officer can be affiliated with multiple firms in corporate records we keep only those cases where the first officer is affiliated with only one firm. We follow the same general approach as in step 5 except that we

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

Linking restaurant owners to voter registration

We combine two snapshots of Florida voter registration data: January 31, 2017 and January 31, 2021.²⁵ The most recent snapshot accounts for 89% of all voter records. The older snapshot includes voters who may have been deregistered for various reasons.

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

1. Drop restaurants whose first officer is not a person or whose first officer has an out-of-state mailing address.
2. Parse officer name into components: last, first, middle, suffixes and credentials.
3. Match based on county, first and last names.²⁶
 - (a) If both owner and voter have middle initials, check that the initials agree. If they do not, drop potential matches. Note that we do not rule out matches where only one of the names includes middle initial or name.
 - (b) Similarly, if both owner and voter names include a suffix like Jr or II, check for agreement and drop potential that disagree.

²⁵ <https://dos.myflorida.com/elections/data-statistics/voter-registration-statistics/voter-extract-disk-request/>

²⁶ We map ZIP codes into counties using [HUD USPS ZIP Code Crosswalk Files](#). In rare cases where a ZIP belongs to multiple counties, we use the counties that accounts for the largest share of the ZIP code.

- (c) If there is a unique match, keep it.
4. If there are multiple matches, try to break ties using city and street address.
 - (a) Drop potential matches whose city does not match.
 - (b) Calculate similarity score between street addresses. Keep the best match if its similarity score is at least 0.80 and is at least 0.05 larger than the next highest similarity score.
 5. If after the previous step there are still multiple potential matches, but they all report the same race, use that race.

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, intensity 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 <code>att7</code>) We calculate county-level average across all white respondents taking the test between 2008 and 2019. County-level racial bias is standardized to have zero mean and standard deviation equal to one.
Implicit racial bias	Overall score on the Race Implicit Association Test (variable name <code>D.biép.White_Good.all</code>). 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 <code>B02001.001E</code>) is from the 2019 American Community Survey.
White population share	Estimate of white alone population (variable name <code>B02001.002E</code>) divided by estimate of total population (variable name <code>B02001.001E</code>) from the 2019 American Community Survey.

Table A1
Table A1—*Continued*

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

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

Table A3
Robustness to Controlling for County Characteristics

This table shows the robustness of the results in Table 6 to controlling for the interaction between *Black* and county characteristics. Regressions are weighted by the number of white respondents to the Race Implicit Association Test during 2008–2019 period. Education gap is the difference between the share of white population with at least a high school and the share of Black population with at least a high school degree. Standard errors are adjusted for clustering by county. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. Except for the number of employees, 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	−0.183*** (0.054)	−0.202*** (0.047)	−0.255*** (0.033)	−0.217*** (0.033)	0.071* (0.038)	0.014 (0.042)	0.034 (0.044)	0.023 (0.044)
Hispanic	−0.031 (0.022)	−0.031 (0.022)	−0.021 (0.028)	−0.021 (0.028)	−0.011 (0.006)	−0.011 (0.006)	0.060*** (0.017)	0.060*** (0.017)
Asian	0.002 (0.014)	0.002 (0.014)	−0.058*** (0.021)	−0.058*** (0.021)	0.060*** (0.016)	0.060*** (0.016)	0.004 (0.036)	0.004 (0.036)
Other	−0.007 (0.035)	−0.007 (0.035)	−0.041 (0.031)	−0.041 (0.030)	0.034 (0.022)	0.034 (0.022)	0.053** (0.022)	0.053** (0.022)
Female	−0.010 (0.007)	−0.010 (0.007)	−0.027*** (0.007)	−0.027*** (0.007)	0.016* (0.009)	0.016* (0.009)	−0.003 (0.012)	−0.003 (0.012)
Black × Bias	0.027 (0.097)	0.091 (0.104)	−0.126** (0.053)	−0.125* (0.074)	0.154* (0.078)	0.216** (0.095)	−0.039 (0.052)	0.098 (0.097)
Black × White population share	0.105 (0.071)	0.081 (0.078)	0.051 (0.047)	0.057 (0.056)	0.054 (0.040)	0.023 (0.044)	0.052 (0.054)	0.006 (0.055)
Black × Ln(Population)	0.236** (0.096)	0.219** (0.107)	0.107* (0.054)	0.132* (0.067)	0.129* (0.075)	0.087 (0.074)	0.024 (0.052)	0.006 (0.059)
Black × Income gap	0.002 (0.049)	−0.004 (0.050)	−0.004 (0.036)	−0.011 (0.037)	0.005 (0.036)	0.007 (0.034)	0.122** (0.046)	0.106** (0.046)
Black × Education gap	−0.096*** (0.028)	−0.112*** (0.035)	−0.058* (0.034)	−0.040 (0.036)	−0.038* (0.021)	−0.072** (0.028)	0.006 (0.040)	−0.015 (0.038)
Black × Unemployment gap	−0.014 (0.046)	−0.007 (0.043)	0.010 (0.050)	−0.001 (0.049)	−0.023 (0.033)	−0.006 (0.039)	−0.022 (0.052)	−0.016 (0.049)
Ln(Seats)	0.040*** (0.006)	0.040*** (0.006)	0.044*** (0.006)	0.044*** (0.006)	−0.005 (0.004)	−0.005 (0.004)	0.003 (0.005)	0.003 (0.005)
Ln(Firm age)	0.034*** (0.005)	0.034*** (0.005)	0.041*** (0.004)	0.041*** (0.004)	−0.007* (0.003)	−0.007* (0.003)	−0.015* (0.008)	−0.015* (0.008)
Accepts credit cards	0.166*** (0.033)	0.166*** (0.033)	0.136*** (0.035)	0.136*** (0.035)	0.030*** (0.010)	0.030*** (0.010)	0.089* (0.048)	0.088* (0.048)
Missing credit cards	−0.020 (0.033)	−0.020 (0.033)	−0.005 (0.025)	−0.005 (0.025)	−0.015 (0.014)	−0.015 (0.014)	−0.006 (0.012)	−0.005 (0.012)
Ln(Reviews)	0.036*** (0.007)	0.036*** (0.007)	0.035*** (0.010)	0.035*** (0.010)	0.000 (0.004)	0.001 (0.004)	0.018 (0.013)	0.018 (0.013)
Average rating	0.000 (0.017)	0.000 (0.017)	0.002 (0.015)	0.002 (0.014)	−0.001 (0.006)	−0.001 (0.006)	0.043** (0.019)	0.043** (0.019)
No reviews	−0.070 (0.078)	−0.070 (0.078)	−0.057 (0.064)	−0.056 (0.064)	−0.014 (0.032)	−0.014 (0.032)	0.093* (0.048)	0.095* (0.048)
Ln(Page views)	0.005 (0.012)	0.005 (0.012)	0.005 (0.009)	0.005 (0.009)	0.001 (0.010)	0.001 (0.010)	−0.006 (0.014)	−0.006 (0.014)
Ln(Photos)	0.039*** (0.009)	0.039*** (0.009)	0.049*** (0.008)	0.049*** (0.008)	−0.010 (0.008)	−0.010 (0.008)	−0.009 (0.012)	−0.009 (0.012)
Bank UCC loan	0.040*** (0.015)	0.040*** (0.015)	0.063*** (0.019)	0.063*** (0.019)	−0.023*** (0.006)	−0.023*** (0.006)	0.054*** (0.011)	0.054*** (0.011)
Nonbank UCC loan	0.048*** (0.016)	0.048*** (0.016)	0.013 (0.014)	0.013 (0.014)	0.035*** (0.012)	0.035*** (0.012)	0.106*** (0.012)	0.106*** (0.012)
R^2	0.171	0.171	0.180	0.180	0.103	0.103	0.098	0.098
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table A4
Gender-Career Bias

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

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

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

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

Table A5
Robustness

This table shows the robustness of the results to a number of alternative specifications. Columns 1 and 4 restrict the sample to single-restaurant firms. Columns 2 and 5 classify a firm as having received PPP loans if any of its affiliates receive PPP loans. Columns 3 and 6 use 4,183 Census block group instead of 820 ZIP code fixed effects. Robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	PPP			Bank PPP		
	Single restaurant firms (1)	Loans to affiliates (2)	Census block group (3)	Single restaurant firms (4)	Loans to affiliates (5)	Census block group (6)
Black	-0.088*** (0.029)	-0.125*** (0.028)	-0.080* (0.042)	-0.155*** (0.028)	-0.181*** (0.027)	-0.155*** (0.040)
Hispanic	-0.037** (0.015)	-0.047*** (0.014)	-0.001 (0.020)	-0.035** (0.016)	-0.043*** (0.015)	-0.016 (0.021)
Asian	0.021 (0.016)	-0.001 (0.015)	0.023 (0.023)	-0.051*** (0.018)	-0.070*** (0.017)	-0.047* (0.025)
Other	-0.016 (0.025)	-0.023 (0.024)	-0.017 (0.036)	-0.039 (0.026)	-0.053** (0.025)	-0.043 (0.036)
Female	-0.006 (0.011)	-0.019* (0.010)	0.001 (0.015)	-0.014 (0.011)	-0.028*** (0.011)	-0.008 (0.015)
<i>N</i>	9,271	9,980	9,980	9,271	9,980	9,980
<i>R</i> ²	0.192	0.192	0.501	0.200	0.207	0.507
Controls	✓	✓	✓	✓	✓	✓
ZIP FEs	✓	✓		✓	✓	
Census block group FEs			✓			✓

Table A6
UCC Borrowing Relationships

This table reports the full output of the regressions in Table 5.

	PPP			Bank PPP			Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Black	-0.098***	-0.099***	-0.070**	-0.166***	-0.164***	-0.144***	0.067***	0.065***	0.075***	0.054*	0.050*	0.049
	(0.028)	(0.028)	(0.031)	(0.027)	(0.027)	(0.029)	(0.019)	(0.019)	(0.021)	(0.029)	(0.029)	(0.031)
Hispanic	-0.032***	-0.030***	-0.029*	-0.035***	-0.032**	-0.032*	0.003	0.002	0.003	0.042***	0.043***	0.041**
	(0.015)	(0.015)	(0.017)	(0.015)	(0.015)	(0.017)	(0.008)	(0.008)	(0.008)	(0.016)	(0.016)	(0.017)
Asian	0.007	0.014	0.013	-0.067***	-0.059***	-0.063***	0.074***	0.076***	0.076***	0.014	0.023	0.013
	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.019)	(0.011)	(0.011)	(0.012)	(0.018)	(0.018)	(0.019)
Other	-0.011	-0.007	0.011	-0.043*	-0.040	-0.025	0.032**	0.033**	0.036**	0.047*	0.052*	0.055*
	(0.025)	(0.025)	(0.028)	(0.026)	(0.026)	(0.029)	(0.015)	(0.015)	(0.017)	(0.027)	(0.027)	(0.030)
Female	-0.007	-0.005	-0.008	-0.017	-0.015	-0.012	0.010*	0.010	0.005	-0.005	-0.002	0.003
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.006)	(0.006)	(0.007)	(0.011)	(0.011)	(0.013)
Ln(Seats)	0.049***	0.045***	0.058***	0.055***	0.050***	0.062***	-0.006*	-0.006*	-0.004	0.012**	0.006	0.009
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)	(0.006)
Ln(Firm age)	0.036***	0.033***	0.037***	0.043***	0.040***	0.043***	-0.008***	-0.007***	-0.006*	-0.014**	-0.018***	0.013**
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)
Accepts credit cards	0.188***	0.178***	0.175***	0.161***	0.150***	0.149***	0.028	0.027	0.026	0.088**	0.073*	0.073*
	(0.041)	(0.041)	(0.040)	(0.041)	(0.040)	(0.040)	(0.017)	(0.017)	(0.017)	(0.038)	(0.039)	(0.039)
Missing credit cards	-0.012	-0.015	-0.014	-0.007	-0.010	-0.009	-0.005	-0.004	-0.005	-0.007	-0.011	-0.011
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.011)	(0.011)	(0.011)	(0.022)	(0.022)	(0.022)
Ln(Reviews)	0.046***	0.044***	0.044***	0.046***	0.044***	0.044***	-0.000	0.000	-0.000	0.013	0.010	0.010
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)	(0.005)	(0.011)	(0.011)	(0.011)
Average rating	-0.021**	-0.019*	-0.020**	-0.015	-0.012	-0.014	-0.007	-0.006	-0.006	0.032***	0.037***	0.036***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)
No reviews	-0.154***	-0.144***	-0.147***	-0.119***	-0.110**	-0.112**	-0.035	-0.034	-0.035	0.103**	0.118***	0.117***
	(0.044)	(0.044)	(0.044)	(0.045)	(0.044)	(0.044)	(0.024)	(0.024)	(0.024)	(0.045)	(0.046)	(0.045)
Ln(Page views)	0.001	0.001	0.001	-0.007	-0.006	-0.006	0.008	0.007	0.007	0.003	0.003	0.003
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)	(0.012)
Ln(Photos)	0.040***	0.037***	0.038***	0.052***	0.049***	0.050***	-0.012***	-0.012***	-0.012***	-0.005	-0.008	-0.007
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.008)
Bank UCC loan	0.053***	0.072***	0.077***	0.101***	0.077***	0.101***	-0.024***	-0.029***	-0.029***	0.054***	0.091***	0.091***

(Continued)

Table A6—continued

	PPP			Bank PPP			Nonbank PPP			EIDL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Nonbank UCC loan		(0.012) 0.054***	(0.019) 0.077***		(0.013) 0.024*	(0.021) 0.034*		(0.006) 0.030***	(0.010) 0.043***		(0.014) 0.108***	(0.025) 0.139***
Black \times Bank UCC loan		(0.012) -0.182*	(0.017) (0.100)		(0.014) (0.099)	(0.019) -0.253**		(0.008) (0.076)	(0.012) 0.071		(0.015) (0.122)	(0.022) 0.171
Hispanic \times Bank UCC loan			0.027 (0.033)		0.004 (0.035)			0.023 (0.018)			0.070*	(0.041)
Asian \times Bank UCC loan			0.055 (0.042)		-0.007 (0.054)			0.062 (0.042)			0.171***	(0.060)
Other \times Bank UCC loan			-0.069 (0.069)		-0.023 (0.069)			-0.046** (0.022)			-0.035 (0.075)	
Female \times Bank UCC loan			0.033 (0.028)		0.018 (0.030)			0.015 (0.016)			0.017 (0.035)	
Ln(Seats) \times Bank UCC loan			-0.073*** (0.013)		-0.075*** (0.013)			0.002 (0.006)			-0.015 (0.015)	
Ln(Firm age) \times Bank UCC loan			-0.021 (0.013)		-0.019 (0.013)			-0.002 (0.006)			-0.036** (0.016)	
Black \times Nonbank UCC loan			-0.097 (0.076)		0.015 (0.079)			-0.112** (0.046)			-0.079 (0.083)	
Hispanic \times Nonbank UCC loan			-0.013 (0.033)		0.017 (0.037)			-0.030 (0.022)			-0.062 (0.040)	
Asian \times Nonbank UCC loan			-0.011 (0.047)		0.072 (0.055)			-0.083** (0.037)			-0.062 (0.061)	
Other \times Nonbank UCC loan			-0.052 (0.075)		-0.073 (0.079)			0.021 (0.056)			0.022 (0.084)	
Female \times Nonbank UCC loan			-0.012 (0.029)		-0.044 (0.033)			0.032 (0.021)			-0.058 (0.036)	
Ln(Seats) \times Nonbank UCC loan			-0.023* (0.013)		-0.007 (0.014)			-0.016* (0.008)			-0.006 (0.016)	
Ln(Firm age) \times Nonbank UCC loan			-0.030**		-0.017			-0.013			-0.009	

(Continued)

Table A6—*continued*

	PPP		Bank PPP			Nonbank PPP			EIDL			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
UCC bank's PPP intensity			(0.015)			(0.017)			(0.010)			(0.019)
			0.004			0.006			-0.002			-0.023***
			(0.006)			(0.006)			(0.003)			(0.008)
R^2	0.179	0.183	0.188	0.191	0.195	0.199	0.109	0.112	0.115	0.100	0.107	0.111
ZIP FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓