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RACIAL DISPARITIES IN ACCESS TO SMALL BUSINESS CREDIT: EVIDENCE FROM THE PAYCHECK PROTECTION PROGRAM

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ABSTRACT

We explore the sources of racial disparities in small business lending by studying the $806 billion Paycheck Protection Program (PPP), which was designed to support small business jobs during the COVID-19 pandemic. PPP loans were administered by private lenders but federally guaranteed, largely eliminating unobservable credit risk as a factor in explaining differential lending by race. We document that even after controlling for a firm’s zip code, industry, loan size, PPP approval date, and other characteristics, Black-owned businesses were 12.1 percentage points (70% of the mean) more likely to obtain their PPP loan from a fintech lender than a traditional bank. Among conventional lenders, smaller banks were much less likely to lend to Black-owned firms, while the Top-4 banks exhibited little to no disparity after including controls. We use novel data to show that the disparity is not primarily explained by differences in pre-existing bank or credit relationships, firm financial positions, fintech affinity, borrower application behavior, or racial differences in rates of fraudulent PPP applications. In contrast, we document that Black-owned businesses’ higher rate of borrowing from fintechs compared to smaller banks is particularly large in places with high anti-Black racial animus, pointing to a potential role for discrimination in explaining some of the racial disparities in small business lending. We find evidence that when small banks automate their lending processes, and thus reduce human involvement in the loan origination process, their rate of PPP lending to Black-owned businesses increases, with larger effects in places with more racial animus.

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In recent years, policy makers in the U.S. and elsewhere have become increasingly concerned about differences across racial groups in access to financial services such as consumer and small business credit (Crutsinger, 2021; Abrams, 2021; Crowell, 2021). Understanding the determinants of observed racial differences in credit access has been challenging due to the difficulty of disentangling the role of credit risk from a possible independent role of race through channels such as preference-based discrimination. In this paper, we study how and why lenders differed in their propensity to extend Paycheck Protection Program (PPP) loans to small businesses owned by members of various racial and ethnic groups. The PPP was established as part of the CARES Act, passed in March 2020, and was designed to help small businesses struggling during the COVID-19 pandemic. With a volume of $806 billion, it is one of the largest single public finance programs in U.S. history.

The design of the PPP makes it an attractive setting to study racial disparities in access to small business credit. The Small Business Administration (SBA) did not issue specific guidance on loan distribution, leaving the private financial institutions administering the loans to independently determine which businesses to serve. As a result, institutional factors that determine banks' regular lending decisions may have also affected PPP loan originations. Importantly for our research design, PPP loans were fully guaranteed by the federal government, and the loan amount was based solely on payroll, largely eliminating credit risk and concerns about selection on other dimensions, such as loan size, from banks' lending decisions. When combined with information on other important determinants of lending decisions, such as firm-level banking relationships and firm cash flows, the PPP data can therefore shed light on the role of race and ethnicity in the lending decisions of different private lenders.

We work with public administrative data from the SBA on 11.8 million loans made between April 3, 2020 and May 31, 2021. In our analysis, we restrict the sample to "first draw" loans (some firms were eligible for two loans) and to loans made before February 24, 2021, when the program's rules changed to explicitly prioritize lending to small firms and minorities. Within this sample of 5.7 million loans, we build on a well-established literature to predict a business owner's race and ethnicity using information such as the owner's name and location (Imai and Khanna, 2016; Humphries et al., 2019; Tzioumis, 2018). We gather owner names from business registrations in collaboration with the data analytics firm Middesk. To improve the prediction, we train a random forest model on the subset of PPP loans in which the borrower reports their race. Our model performs well at predicting self-reported race in a hold-out sample of PPP borrowers not used to train the model. This assigned race should be interpreted as a signal that is highly correlated with self-reported race and contains important socioeconomic content, consistent with studies showing discrimination against job applicants with "African American-sounding" names (Bertrand and Mullainathan, 2004; Milkman et al., 2012; Bartoš et al., 2016).[1] Using this approach, we assign race and ethnicity to the business owner for 4.2 million PPP loans.

We document substantial variation across different types of financial institutions in the propensity to

[1]As we discuss in more detail below, in those instances in which the self-reported race differs from the predicted race, it is plausible that many loan officers, who usually do not have access to borrowers' true race but observe the inputs to the algorithm, would treat borrowers in a way that is more aligned with the signal than with self-reported race. For example, a number of borrowers with the last name "Huang" self-report to be Black but are assigned "Asian" by the algorithm.

extend PPP loans to Black-owned businesses. Within the analysis sample, about 8.6% of all loans and 2.9% of loans to employer businesses went to Black-owned businesses. Traditional banks made between 3.3% (among small banks) and 7.8% (Wells Fargo) of their PPP loans to Black-owned businesses. On the other hand, fintech lenders made 26.5% of their PPP loans to Black-owned businesses. Overall, fintech lenders were responsible for 53.6% of PPP loans to Black-owned businesses, while only accounting for 17.4% of all PPP loans in the analysis sample. There are also differences across lenders in the propensity to lend to White-, Asian- and Hispanic-owned firms. However, the difference in lending between conventional lenders and fintech lenders is most striking for Black-owned businesses, and this disparity is the focus of our paper.

We first consider important dimensions along which Black-owned businesses differ from other firms. For example, their average PPP loan amount of $24,315 is less than half of that for Asian- and Hispanic-owned businesses, and one-quarter of that for White-owned businesses. Since PPP lenders were compensated with 5% of the loan value for loans under $350,000, the presence of fixed costs or capacity constraints creates an incentive to prioritize the largest loans. If fintech lenders have smaller fixed costs or more capacity, this could explain their disproportionate lending to smaller, Black-owned firms. We therefore add granular controls for loan size. We also control for loan approval date and borrower characteristics such as zip code, industry, business organizational form, and employer status.[2] Overall, about two-thirds of the unconditional difference in Black-owned businesses' propensity to get fintech PPP loans relative to loans from other lenders is explained by differences in these characteristics.

However, even with these controls, which hold the profitability of lending and the availability of bank branches fixed, we find that Black-owned businesses are 12.1 percentage points more likely to obtain their PPP loans from a fintech firm than from traditional lenders relative to the mean probability of obtaining a fintech PPP loan of 17.4%. Much of this effect is substitution away from non-Top-4 banks—especially small- and medium-sized banks—towards fintech lenders by Black-owned businesses.[3] For Top-4 banks, we do not find a large difference in the propensity to extend PPP loans to Black-owned businesses after including loan-level and firm-level controls. In this paper, we analyze what might explain the remaining large disparity between Black-owned firms and other businesses in the propensity of getting a PPP loan from a fintech firm rather than a smaller conventional lender.

First, observers of the PPP program have noted that banks tended to prioritize their own clients' PPP loan applications, which may have distorted allocations away from the government's intended "first come, first serve" approach (Cowley, 2021; Li and Strahan, 2020). If banks indeed prioritized PPP loan applications from their own clients, and if Black-owned businesses did not bank with active PPP lenders (in particular among the small banks), this could explain some of the observed differences in their propensity to eventually borrow from other lenders such as fintech firms. To assess whether this channel

[2] Adding zip code fixed effects suggests that traditional lenders are less likely than fintechs to make loans to businesses—even White-owned ones—in predominantly minority communities. While our paper focuses on explaining the disparity in lending patterns conditional on observable characteristics such as location, understanding why different lenders have different propensities to extend loans to any firms located in high-minority neighborhoods is an important question for future research.

[3] When we consider lending to the other races and ethnicities in our fully controlled models, we find that small- and medium-sized banks in particular were more likely to lend to White-owned businesses.

can explain the observed disparity, we match the PPP data to novel bank statement data from Ocrolus, a firm that digitizes and analyzes financial documents for financial institutions. These bank statements, which are available for about 170,000 PPP borrowers in our analysis sample, include information on bank and credit relationships as well as cash flows. Within this matched sample—which selects on having a checking account and a past fintech loan application—Black ownership is associated with a 5.5 percentage point higher probability of obtaining a PPP loan through a fintech lender, conditional on controls. This disparity is unaffected by adding fixed effects for the identity of the bank where a borrower has their primary business checking account. In other words, even though we find that banks generally served their own clients at higher rates, this fact does not explain the higher rate of fintech PPP loans for Black-owned businesses.

The bank-statement data also allows us to further explore why Black-owned businesses were more likely to borrow from fintechs rather than smaller banks. In analyses that restrict the sample to firms with checking accounts at different types of banks, we identify two channels through which Black-owned businesses shifted to borrowing from fintechs rather than smaller banks. First, Black-owned firms banking outside the top-4 banks were less likely to get their PPP loans from their checking account banks. Second, among those firms that got PPP loans outside their checking account banks, Black-owned firms were less likely to obtain loans from smaller banks, and more likely to obtain them from fintech lenders instead. Quantitatively, this second channel, which captures racial differences in the rates of establishing new bank relationships with different types of lenders, explains the majority of the residual disparity.

We next explore whether borrowers' financial conditions can explain the relatively higher probability of Black-owned businesses of obtaining PPP loans from fintech firms instead of smaller banks. Even though PPP loans were fully guaranteed by the federal government, some traditional lenders may have preferred lending to better-performing businesses that would be more attractive future clients. In addition, loan officers at these banks, who are used to screening for creditworthiness, may have preferred businesses with better financial positions as they do in their usual course of business, even if a borrower's financial performance would not directly affect the profitability of a given PPP loan. We assess this possibility using monthly data from Enigma on firms' credit and debit card revenues, focusing on the period immediately prior to loan approval. In the matched sample of 820,000 firms, adding fixed effects for percentiles of card revenue during the PPP loan approval month and the two previous months has no effect on the observed propensity of Black-owned firms to receive their PPP loans from fintech lenders. Controlling for bank statement cash flows observed in the Ocrolus data also does not affect the disparity. While both the card revenue and bank statement samples are not entirely representative—in particular, they skew towards larger or more sophisticated firms—the fact that the disparity persists in these samples is evidence of its importance across a wide range of small businesses.

A third possible explanation for the racial disparities in lending outcomes is firm application behavior rather than lender decision-making. For example, it could be that Black-owned businesses prefer fintech lenders and thus applied to these lenders at higher rates. This is unlikely given that we also observe a disparity within a sample of firms with prior fintech loan applications which holds fixed a certain degree of fintech affinity. Nonetheless, to further assess this possibility, we obtain PPP application data from the marketplace lending platform Lendio. Lendio routed some PPP applications to conventional lenders, some to fintech lenders, and some to both (routing was random conditional on loan size, geography, and capacity criteria set by the lender partners). We find that even within a sample of about 46,000 PPP loan applications that Lendio sent only to conventional lenders, Black-owned businesses were 3.9 percentage points more likely to end up with a fintech PPP loan. This offers evidence consistent with the hypothesis that conventional lenders more often reject applications from Black-owned businesses, pushing these firms to subsequently apply to fintechs.

We also consider whether higher rates of fraudulent PPP applications from Black-owned businesses combined with systematically looser compliance standards at fintechs could explain our results. Using 268 unsealed PPP fraud cases prosecuted by the U.S. Department of Justice, we find that the Black-owned share among fraudulent loans is 8.4%, which is almost exactly the Black-owned share of the full sample (8.6%). Therefore, it would have been incorrect to statistically discriminate on race to screen for fraudulent behavior.[4] More generally, a fraud channel is implausible because, as we discuss below, the CARES Act and subsequent regulation indemnify lenders against liability for borrower failure to comply with the program rules; to our knowledge, the government has thus far brought no cases against lenders.

The final mechanism that we consider is the role of human decision-making, which could enable preference-based discrimination against Black borrowers. To explore this possibility, we examine how the propensity of Black-owned businesses to obtain fintech loans varies with measures of racial discrimination. Using six measures of anti-Black racial animus—including racially biased Google searches, implicit and explicit bias tests, and measures of local housing segregation—we find that the tendency of Black-owned businesses to borrow from fintech lenders instead of smaller conventional lenders is consistently higher in areas with more racial animus, even after controlling for firm and loan characteristics. These results suggest that preference-based discrimination might explain at least some of the substitution of Black-owned businesses towards fintech and away from smaller banks.

Automation of the loan application and approval process could help account for the absence of disparate treatment by race at the Top-4 banks (after including controls) and the high rate of lending to Black-owned firms at fintechs. Fintech lenders almost fully automate their underwriting processes, leaving little scope for preference-based discrimination to affect the approval decision. In contrast, conventional lenders traditionally rely more on human involvement and personal relationships between loan officers and clients (Petersen and Rajan, 1994; Berger and Black, 2011). However, there is sizable variation in the degree of automation across conventional lenders, with larger banks—those where we see little difference in the conditional probability of lending to Black-owned businesses—being more automated than smaller banks.[5] Consistent with an important role of automated lending systems in

[4] Consistent with Griffin et al. (2021), fintechs make up a disproportionate share of the fraudulent loans, at 46%. Small banks made a larger share of the fraudulent loans (24%) than top banks (13%), which could be consistent with better compliance infrastructure at the top banks.

[5] For example, one news article notes that "Large banks have avidly adopted robotic process automation...It's tougher for smaller banks to follow suit" (Crosman, 2020). As a second example, a 2018 Fannie Mae survey found that 76% of large banks but only 47% of small banks were familiar with artificial intelligence or machine learning technology.

explaining our findings, we show that when small banks automated their loan origination procedures during the PPP period, their rate of lending to Black-owned businesses increased relative to other small banks that did not automate their processes. A differences-in-differences analysis shows that automation more than doubled small banks' propensity to lend to Black-owned businesses, with larger effects in locations with higher racial animus. These findings support the conjecture that automation might help reduce racial discrimination in the loan origination process.

Despite our findings suggesting an important role of taste-based discrimination in explaining some of the observed patterns, there may be other remaining explanations for the residual racial gap in the probability of borrowing from different lenders. Having said this, it is unclear how a mechanism besides discrimination would account for the larger racial gap in areas with higher racial animus. In addition, our controls for firm size, location, industry performance, and pre-existing banking and credit relationships account for most possible explanations. It is also important to highlight that many of the variables we control for in our regressions—such as the location of bank branches or the distribution of which firms have checking accounts at banks—may themselves be the result of historical patterns of discrimination. In other words, it is possible that the substantial differences in our controlled models represent a lower bound estimate of the overall effect of discrimination on lending patterns.

Several contemporaneous papers offer results consistent with ours. Erel and Liebersohn (2020) show that fintech lenders tended to extend more PPP loans in areas with higher minority population shares. Fairlie and Fossen (2021) also use geographic variation to find that total PPP loan flows were negatively correlated with the minority share of the population. Relative to these papers, we demonstrate that even within a given geography, fintech lenders disproportionately lent to Black-owned firms, showing that bank branch location cannot fully explain the observed patterns. In addition, we make progress on identifying the mechanisms, ruling out that the patterns are largely explained by differential banking relationships, financial performance, or application behavior, and finding evidence consistent with preference-based discrimination among smaller banks without automated lending processes. Chernenko and Scharfstein (2021) study PPP lending in a sample of nearly 11,000 restaurants in Florida, for which they can link owner names to voter registration records. They show that minority-owned businesses are more likely to get non-bank PPP loans and conclude that racial bias seems to explain the lending differences. Our paper benefits from vastly larger and richer data that is more representative of PPP borrowers across geographies and industries. In addition, our use of checking account data, credit card data, and loan application data allows us to directly assess a variety of possible explanations in addition to discrimination. Finally, our analysis of cross-sectional and time-series variation in the lending behaviors of different conventional lenders allows us to show that the degree of automation in the lending process is a key factor in explaining the observed patterns.

More broadly, we contribute to the understanding of racial disparities in access to financial services. This literature has mainly studied residential mortgage and consumer credit markets (Tootell, 1996; Bayer et al., 2018; Dobbie et al., 2020; Bhutta and Hizmo, 2021; Ambrose et al., 2020; Giacoletti et al., 2021; Begley and Purnanandam, 2021; Blattner and Nelson, 2021). While there is extensive work on bias against Black people across a wide variety of settings (e.g., Arnold et al., 2018; Bertrand and Mullainathan, 2004; Knowles et al., 2001; Anwar and Fang, 2006; **?**; Price and Wolfers, 2010), there is less work on discrimination against Black business owners. Blanchflower et al. (2003) find racial differences in access to small business credit, while Robb and Robinson (2018) do not find such differences. Other work on the role of race in small business lending includes Fairlie and Robb (2007), Asiedu et al. (2012), Bellucci et al. (2013), and Fairlie et al. (2020).

Our work also relates to a literature studying how the COVID-19 pandemic and associated policy responses affected small businesses (Alekseev et al., 2020; Bartik et al., 2020a; Fairlie, 2020; Greenwood et al., 2020; Kim et al., 2020). Much of the work on the PPP focuses on the effectiveness of the program in mitigating job loss (Hubbard and Strain, 2020; Faulkender et al., 2020; Granja et al., 2020; Autor et al., 2020; Bartik et al., 2020b; Barraza et al., 2020; Bartlett and Morse, 2020). Other researchers have examined whether firm size or pre-existing banking relationships can explain access to PPP loans (Humphries et al., 2020; Li and Strahan, 2020). Finally, we add to a literature that assesses the role of fintech firms in the financial system (Seru, 2019; Philippon, 2019; Federal Reserve, 2020; Ranson, 2020; Gopal and Schnabl, 2020). Most directly related is a literature that has explored the role of fintech lenders in extending credit to traditionally underserved minorities (Tang, 2019; Balyuk et al., 2020; Fuster et al., 2019; Buchak et al., 2018; Berg et al., 2020; Bartlett et al., 2021; D'Acunto et al., 2020).

1 The Paycheck Protection Program: Setting and Data

The Paycheck Protection Program (PPP) was first established as part of the Coronavirus Aid, Relief and Economic Security Act ("CARES Act"), passed on March 27, 2020. The PPP provided government-guaranteed loans to firms which certified that their businesses were "substantially affected by COVID-19." Private lenders were fully responsible for targeting the funds and determining which PPP applications to prioritize. The Small Business Administration (SBA) approved lenders and individual loans, which primarily involved a duplication check to avoid granting multiple loans to a single entity. Although Section 1102 of the CARES Act specifies that the program should prioritize "small business concerns owned and controlled by socially and economically disadvantaged individuals," this was a non-binding "Sense of the Senate" portion of the legislation. Media reports early in the life of the PPP program raised concerns that banks were turning away large numbers of PPP applications from minority-owned businesses (Simon and Rudegeair, 2020; Zhou, 2020; Beer, 2020).

The initial CARES Act authorized \$349 billion in loan guarantees for the PPP, and issuance began on April 3, 2020. Demand for PPP loans vastly exceeded expectations, and funding for the initial program ran out on April 16, 2020. Congress approved a second PPP tranche of \$310 billion on April 24, 2020, and its distribution began on April 27, 2020. A third tranche of \$284.5 billion was approved on December 27, 2020. In this round, firms were eligible to receive a "second draw" loan if they met certain conditions. By the time the program closed permanently at the end of May 2021, 11.5 million loans, administered by 5,467 lenders and totaling more than \$800 billion, had been approved.

PPP Loan Policy and Lender Intermediation. PPP loans were 100% government-guaranteed and uncollateralized. The loan amount was fixed at 2.5 times monthly pre-COVID payroll. A PPP loan was forgiveable—turning into a grant—if the business used it for eligible expenses within six months of receiving it; 60% of the amount had to be spent on payroll, and the rest could be spent on items such as rent, utilities, and mortgage interest. As of November 7, 2021, 72% of loans and 77% of loan value had already been forgiven (see SBA Forgiveness Website). In the event that a loan was not forgiven, repayment would begin after the six months in which the loan had to be used *plus* a 10-month grace period. At that point, loan maturity was two years at 1% interest.

The SBA compensated lenders for originating and servicing PPP loans according to the following graduated, upfront fee system, creating incentives for lenders to prioritize larger loans:

- 5% for loans of not more than \$350,000;
- 3% percent for loans of more than \$350,000 and less than \$2,000,000; and
- 1% percent for loans of at least \$2,000,000.

Lenders were widely reported to face capacity constraints as a result of their pre-existing loan infrastructure. Lenders participated voluntarily in the PPP, and they entered and left the program over time. Fintechs tended to enter somewhat later for several reasons. Some required special approval because they were not regulated insured depository institutions or pre-approved SBA lenders. Others did not have large enough balance sheets to originate many PPP loans and needed to wait for the PPP Liquidity Facility established by the Federal Reserve to come online, which only occurred several weeks after the program began. This facility enabled banks, and later fintechs, to post PPP loans as collateral for new funds with which to originate loans. Still other fintechs partnered with originating charter banks, such as Celtic, in order to participate. In our analysis below, we control for the week of PPP loan approval to ensure that our results are not affected by the dynamics of lender participation.

Lender Obligations and Risk. In originating PPP loans and processing forgiveness applications, lenders faced lower compliance burdens than when making conventional loans.[6] This reflected the high priority that Congress and the Executive branch placed on getting funds out quickly. Specifically, the program required lenders to accomplish only the following tasks: "Each lender shall:

1. Confirm receipt of borrower certifications contained in Paycheck Protection Program Application form issued by the Administration;
2. Confirm receipt of information demonstrating that a borrower had employees for whom the borrower paid salaries and payroll taxes on or around February 15, 2020;
3. Confirm the dollar amount of average monthly payroll costs for the preceding calendar year by reviewing the payroll documentation submitted with the borrower's application;
4. Follow applicable BSA requirements" (85 FR 20811 III.3.b)

[6]The CARES Act explicitly held lenders "harmless" from any enforcement action related to loan forgiveness: "The lender does not need to independently verify the borrower's reported information if the borrower submits documentation supporting its request for loan forgiveness and attests that it accurately verified the payments for eligible costs" (86 FR 8283).

Here, "BSA" refers to the Bank Secrecy Act, which requires baseline anti-money laundering and know-your-customer measures. Although there was some uncertainty about policy early in the program—this uncertainty is one reason we check that our results are robust to both excluding or restricting to the first few weeks of loan approvals—legal experts were clear that lenders faced minimal enforcement risk. For example, Reginald Harris, partner at Bryan Cave Leighton Paisner LLP, said that:

> "The Bank Secrecy Act puts some responsibility on banks to report suspected fraud to authorities. But the coronavirus relief act that created the PPP made it so that banks would be "held harmless" for borrowers' failure to comply with program criteria" (Duren, 2020).

This was to the benefit of smaller banks, which typically have less robust and less automated compliance infrastructure. David Rybicki, a partner at K&L Gates LLP, said:

> "The CARES Act outlined that the lender was able to rely on data from borrowers...Compliance is often burdensome for small banks that do not have the resources of their larger counterparts. A lot of smaller lenders are participating in part because of the fact that there aren't significant added compliance burdens"(Duren, 2020).

Since the minimization of any credit or other risks in the PPP context is important for our conclusions, it is useful to summarize the lender's risks via a series of questions. First, what happens if borrower doesn't use loan as intended? The loan is not forgiven, and the borrower enters a repayment plan. Second, what happens if a borrower defaults? The loan is 100% government guaranteed, so the lender recoups the loan amount. Third, what happens if the borrower is found ex-post to have committed fraud? The lender's fee is subject to potential clawback, but "SBA's determination of borrower eligibility will have no effect on SBA's guaranty of the loan" (85 FR 33010 3). In sum, lenders faced *de minimis* risk in the PPP, contrasting with other regulated products such as mortgages.

1.1 PPP Data

We obtain information on all PPP loans as of August 15, 2021 directly from the SBA. These data were released following a court order and include the business name and address for all PPP loan recipients, as well as information about the business type, loan size, self-reported number of jobs saved, the loan originator, and the loan servicer. Subsequently, we term the loan originator the "PPP lender." To construct our dataset, we retain only a firm's first loan and drop apparent duplicate loans, so that each firm appears once. Specifically, we begin with a raw dataset from the SBA, which has 11.8 million loan observations. Of these, 2.9 million are tagged as second draws (where a firm legally obtained a second PPP loan). After dropping these, we are left with 8.8 million observations.

We also drop loans made after February 23, 2021. We do this because the Biden Administration made drastic changes to the PPP, the first of which took effect on February 24. These changes included first restricting loans to small firms with less than 20 employees, and then permitting only Community Development Financial Institutions (CDFIs) to use PPP funds. Since our goal is to understand lending behavior in a more representative population of both lenders and borrowers, we drop loans made after February 23, 2021. This leaves us with 5.7 million PPP loans. However, our results are very similar when we use the full time period, as well as when we include second draw loans.

The focus of our analysis is to understand differences by lender type in originating PPP loans to minority-owned businesses. We classify all PPP lenders into the following mutually exclusive groups:

1. The Top-4 banks by assets (JP Morgan Chase, Bank of America, Wells Fargo, and Citibank);
2. Large banks: Banks with more than $100 billion in assets, excluding the Top-4;
3. Medium-sized banks: Banks with more than $2.2 billion in assets (but below $100 billion);
4. Small banks: Banks with less than $2.2 billion in assets;[7]
5. Credit unions: Based on the lender name (i.e., having ”credit union” or ”CU” at end of the name);
6. Community Development Financial Institutions (CDFIs) and nonprofits;[8]
7. Minority Depository Institutions (MDIs): As classified by the FDIC.
8. Fintech lenders: All lenders officially designated as such by the SBA. We further include online lenders who originate primarily for or via fintech partners or platforms, online lenders founded since 2005, and online lenders that received venture capital (VC) investment.[9]

This classification yields 11 mutually exclusive lender types (note each of the Top-4 banks is considered as its own category). Table 1 shows how PPP loan origination varied across these lender types for the full sample (Panel A) and the first-draw sample (Panel B). Focusing on Panel B, traditional banks originated about 75% of PPP loans, with non-Top-4 banks responsible for 59% of all loans. Fintech lenders originated 16.2% of all PPP loans, while credit unions and MDIs each originated about 4%, and CDFIs 2%. Fintech and non-bank lenders made substantially smaller loans. The average (median) PPP loan amount for fintech lenders is $31,921 ($15,500) compared to, for example, $87,182 ($20,833) for small banks. The PPP loans originated by credit unions and Wells Fargo were the next-smallest in both average and median. In Panel A of Appendix Table A.2, we show similar summary statistics for the subset of loans for which we can predict borrower race.

[7]We include the roughly 6,000 loans by Business Development Corporations (BDCs) in the Small Bank category, since these loans behave similarly in terms of the variables we study as the Small Bank loans.

[8]We pool nonprofits with CDFIs because nonprofits issued very few loans (fewer than 15,000) and their loans have similar characteristics as those of the CDFIs.

[9]Appendix Table A.1 lists all lenders we classify as “fintech.” In some cases, the originator listed in the table made loans primarily through fintech partners. For example, all of PayPal’s fintech loans were originated by WebBank, and Square’s loans by Celtic Bank. The only fintech lender with a branch is Cross River. However, Cross River originated an overwhelming quantity of loans for fintech partners such as Kabbage, they were founded in 2008, and received VC funding, so we consider Cross River a fintech lender for our purposes. In the data, we do not observe loan referrals from traditional banks to other lenders, so loans referred to fintech by other lenders would be classified as fintech loans. We also do not observe back-end processors that do not show up as lenders or servicers, including Finastra, Ocrolus, and Customers Bank (which played this role for other lenders even as it was also processing its own PPP loans). So some loans processed by fintech firms but originated by other lenders would be classified according to their ultimate lender.

1.2 Identifying Borrower Race and Ethnicity

A key element of our analysis is identifying the race and ethnicity of the owners of the firms participating in the PPP. The SBA data contains details on owner race for a small and selected subset of PPP borrowers who chose to self-report this information in their loan application, and for which the lender also chose to report this information to the SBA. To identify a signal for race and ethnicity for a larger set of PPP borrowers, we build on a well-established literature to predict race from a business owner's name, and the firm's location, industry, and employer status.

We first identify a borrower firm's individual owner or most senior executive. Our primary source for this information is data on current firm officers as of July 2021 drawn from Secretary of State registrations, provided to us by the analytics firm Middesk. The owner is identified as the first individual listed as owner or principal under "business contacts" in Secretary of State filings. For non-employer firms such as sole proprietorships, we also use the fact that the "business name" reported in the PPP data usually corresponds to the owner's name. Finally, we obtained applicant names for a sample of PPP applicants from Lendio. We combine these data with public SBA information on the businesses' address, industry, and employer status. Utilizing this data, we use a machine learning approach to estimate the conditional probability of a business owner being Asian, Black, Hispanic, or White.

Our process consists of two steps. First, we follow the methodology in Imai and Khanna (2016) by combining the Census list of last names (Word et al., 2008) with the census tracts of business locations to estimate the conditional probability that an individual belongs to a certain racial group given their last name and location.[10] The second step combines the resulting Bayesian posterior probability with the racial distribution of common first names and industries by employer status as features in a random forest model with 1,000 trees (see Tzioumis, 2018; United States Census Bureau, 2012). We train and validate the random forest model on the 809,119 PPP loans with self-reported race, a successfully geolocated address, an identified owner name and information on a firm industry and employer status. The model generates the probability that a borrower belongs to a certain race given first and last name, location, industry, and employer status. We identify the borrower to be of the race with the largest probability across the set of racial groups $\mathcal{R}$. In a robustness test, we restrict the sample to borrowers who have an assigned probability of more than 90% for their most likely races.

In total, we can predict the race for 4.18 million unique PPP borrowers. For the remaining firms, we do not observe owner name or the geolocation fails. We also exclude about 30,000 loans for which the algorithm predicts the owner race to be "Other." We show in Panel A of Appendix Table A.3 that

[10] Suppose we denote the last name and census tract of an individual i as L_i and T_i. The unobservable race or ethnicity of the individual is denoted as R_i, and $\mathcal{R} \in \{Asian, Black, Hispanic, White\}$ is the available set of all such groups. We would like to estimate $Pr(R_i = r|L_i = l, T_i = t)$. The Census list of last names provides the racial and ethnic distribution of 151,671 last names, $Pr(R_i = r|L_i = l)$, which makes up 90% of the population in the 2000 Census. We obtain the racial and ethnic distribution of each census tract from the American Community Survey, which gives $Pr(R_i = r|T_i = t)$ and the population share of each census tract $Pr(T_i = t)$. Assuming that the location and last name of an individual are independent conditional on race and ethnicity, Bayes' rule implies $Pr(R_i = r|L_i = l, T_i = t) = \frac{Pr(T_i=t|R_i=r)Pr(R_i=r|L_i=l)}{\sum_{r' \in \mathcal{R}} Pr(T_i=t|R_i=r')Pr(R_i=r'|L_i=l)}$. Here, $Pr(T_i = t|R_i = r)$ can once again be decomposed using Bayes' Rule, allowing for a probabilistic prediction of an individual's race and ethnicity.

the model correctly predicts the vast majority of the self-reported sample (note that, for most of our analysis, we do not actually use the self-reported race in our analysis, but instead the prediction, so that we consistently capture the signal sent by the name). For example, of those we predict to be Black, 93% self-identify as Black (9.1/9.6 $\approx$ 0.93). To assess the out-of-sample quality of the prediction, which is the most relevant for assessing our ability to predict the race and ethnicity of individuals who did not self-identify, we randomly set aside a "hold-out" sub-sample of borrowers who self-identify race but are not included in the training of the random forest model. Panel B of Appendix Table A.3 contains the confusion matrix of our race prediction within the hold-out sub-sample. It shows that 75% of those business owners that we predict to be Black self-identified as Black (5.7/7.6 $\approx$ 0.75).

We show the probability distribution for each race in Appendix Figure A.1. For example, Panel A contains the set of borrowers whose predicted race is Black (the algorithm assigns Black to have the highest probability across the race and ethnicity options). The graph shows the distribution of the probability of being Black among these observations. Panel D of Appendix Table A.3 summarizes these distributions for each race; among people predicted to be Black, the mean chance of being Black according to the algorithm is 76%, with a median of 80%. In some of our tests, we use this probability (instead of just a race dummy) to provide further evidence for our interpretations of our findings.

It is worth noting that, since loan officers often only have access to borrowers' names and locations (rather than true borrower race), they may respond to the race or ethnicity most associated with a given name, rather than to the borrowers' actual race or ethnicity. For example, two of the prediction algorithm's "errors" are individuals whose last names are Huang and Rodriguez, who identify as Black but are predicted to be Asian and Hispanic, respectively. It is plausible that loan officers observing only applicants' names might also infer an incorrect race for these borrowers, and our algorithmically assigned race may correspond more closely to the race inferred by a loan officer. Such behavior would be highly consistent with findings from audit studies such as Bertrand and Mullainathan (2004), who document discrimination against job applicants with "African American-sounding" names.

We call the sample for which we can identify race the "PPP Analysis Sample." Panel A of Table 2 shows that, within this sample, 8.6% of business owners are Black, 7.5% are Hispanic, 8.9% are Asian, and 75.0% are White. The distributions of originating lender and firm characteristics such as loan amount are similar across the full sample (Table 1, Panel B) and the analysis sample (Table 2). For example, the average PPP loan amount is $93,784 in the full sample and $93,666 in the analysis sample. Appendix Table A.4 confirms that the distributions of firms' business types, locations, and industries are also similar in the full and analysis samples.[11] This highlights that the sample for which we can predict race is broadly representative of the overall PPP population, which, in turn, is relatively representative of privately-owned U.S. businesses on industry and geography (see SBA May 2021 Program Report).

The racial composition of our PPP analysis sample is also comparable to that of the population of

[11] We consolidate business types to seven categories from the 19 organizational forms in the SBA data: corporations, limited liability corporations (LLC), non-profits, self-employed, sole proprietorships, subchapter S corporations, and other. We assign cooperatives and other non-profit organizations under the non-profit umbrella. Independent contractors and self-employed individuals are classified as self-employed, and limited liability partnerships are considered as LLCs. "Other" includes any business types with less than 100,000 observations (such as employee stock ownership plans, joint ventures, etc.)

small business owners in the United States. Appendix Table A.5 repeats Panel A of Table 2 for employers and non-employers, respectively. For example, we predict that 2.9% of employer businesses in the PPP analysis sample are Black-owned, compared to 2.1% of the population of comparable small business owners in the 2012 U.S. Census Bureau Small Business Owners survey (United States Census Bureau, 2012). Among non-employer firms, 18.7% are Black-owned in our sample vs. 11.2% in the population.

1.3 Bank Statement Data

To help distinguish between various explanations for differential lending of banks across races, we acquire data from Ocrolus on borrower firms' bank statements through July 2021. Ocrolus digitizes documents for fintech companies, including bank statements that these lenders use in the underwriting process, and thus has a large repository of business checking account statements. We match around 216,000 unique PPP borrowers in our analysis sample to Ocrolus' database using information on the business name and address. If several bank statements are available for a firm (the average firm has three bank statements, mostly from 2019 and 2020), we focus on the most recent statement prior to the issuance of the PPP loan.

Using information from the bank statements, we determine borrowers' pre-existing banking and credit relationships. We define a firm's checking account bank as the bank that issued the statement.[12] Panel C of Table 1 reports statistics on the whole bank statement-matched sample, organized by PPP lender as in the previous panels. (We repeat Panel C for the subset of loans for which we can predict borrower race in Panel B of Appendix Table A.2.) Within this sample, 28.5% of businesses obtained their PPP loans from their checking account banks. There is sizable heterogeneity across banks. About two-thirds of all PPP loans originated by Bank of America, JP Morgan Chase, and Wells Fargo went to checking account clients of those banks. For other large banks, this number is 50%, and for medium and small banks, it is 39.8% and 23.8%, respectively. Additional variables from these banks' statements are reported in Panel B of Table 3. For example, we find that almost half of all PPP borrowers have their checking accounts at a Top-4 bank, while 16% have checking accounts at other large banks.

The bank statement sample and the full analysis sample are similar on many important dimensions, such as loan amount, which is $80,987 in the bank statement sample and $93,666 in the analysis sample. Bank statement-matched borrowers are more likely to be minority-owned. The main dimension of selection is that firms matched to bank statement data have a much higher rate of fintech PPP loans—36.3%, compared to 17.4% in the analysis sample. This reflects the fact that Ocrolus processes loan applications for many fintech clients, and thus selects a sample of applicants with substantial fintech affinity and experience.

We use text descriptions of transactions in the bank statements to identify credit relationships. Specifically, we use the existence of a transaction to or from a lender to suggest a credit relationship of some sort with this lender (e.g., a loan, credit line, or credit card payment). Among all borrowers, about

[12] When a firm has statements from multiple banks, we identify the primary account as the one with the highest balance. Only 1% of firms have statements from multiple banks.

14.2% had a credit relationship with a fintech firm, while 80.0% had a credit relationship with a traditional bank (Panel B of Table 3). Note that these credit relationships also include business credit cards, and are thus much broader than other sources of data, such as UCC filings for secured debt. The share of firms with access to external financing in the Ocrolus sample is naturally higher than in the population of small businesses as reported by Alekseev et al. (2020), since Ocrolus usually only obtains the bank statements for firms actively seeking external credit. There are no large differences by PPP lender type in the propensity of firms to have prior credit relationships with a fintech or a traditional lender (Table 1, Panel C). In some specifications below, we focus on the sample of firms with a history of obtaining fintech credit, allowing us to rule out that any differential lending by fintech firms to minority-owned businesses in this sample primarily reflects a higher familiarity or experience of minority-owned businesses with fintech lenders in general.

We also use the bank statement data to calculate a firm's monthly cash inflows and outflows as a measure of firm financial performance. Panel B of Table 3 shows that mean net monthly cash inflow across all firms is $9,124, while it is $6,332 among Black-owned businesses.

1.4 Card Revenue Data

To assess whether the real-time financial performance of small businesses helps explain our results, we also gathered data from Enigma on monthly credit and debit card revenues. Enigma is a data analytics company serving enterprise customers. Through a partnership with Verisk, a data warehouse that banks employ to enable cross-issuer fraud checks, Enigma accesses real-time credit and debit card transactions covering more than 60 banks, including all the major issuers. Their data include at least 60% of all U.S. debit and credit card transactions.

About one million PPP borrowers were successfully merged between Enigma's merchant identity platform and the PPP loan data. Enigma provided monthly revenue data for these firms, which amounts to over 70 million observations. For 813,812 of these firms, we observe revenue in the approval month or the two months before (Enigma does not report these numbers if there were too few transactions in a given month). We calculate average revenue across these months. Summary statistics are shown in Panel D of Table 2 and in Panel D of Table 3. Notably, the Enigma-matched firms tend to be larger, with a mean loan amount of $141,529 (compared to $93,666 in the main analysis sample). This reflects Enigma being more likely to establish a merchant identity for firms that appear more frequently in their card transaction data. Consistent with our previous measures for firm size—PPP loan amount and bank statement cash inflows—the average card revenue for Black-owned firms is about half of that for the other groups, at $23,169, compared to $42,557 for Hispanic- and Asian-owned firms, and $58,355 for White-owned firms.

1.5 Other Data

Beyond the datasets described here, we use several further sources of data—including data on loan applications through Lendio, and information on when small banks automated their lending procedures—

to explore the mechanism for our results. These data are described in tandem with the analyses in Sections 3 and 4.

2 Who Lent to Minority Borrowers, and Why?

We begin this section by exploring whether certain types of lenders were more likely to extend PPP loans to borrowers of a particular race or ethnicity. We then ask whether any disparities are explained by three types of baseline characteristics that represent obvious hypotheses for lender differentiation: borrower size, industry, and location. Finally, we examine the role of pre-existing banking and credit relationships, firm financial conditions, and borrower application behavior in explaining any residual differences.

We first illustrate the main descriptive statistics. Panel A of Figure 1 shows the share of PPP loans originated by each lender type made to Black-owned businesses (see also Panel A of Table 2). Only 3.3% of PPP loans originated by small banks went to Black-owned businesses. At large banks, including the Top-4, Black-owned firms represent between 4% and 8% of loan recipients. At the top end of the spectrum, CDFIs made 10.6% and fintech lenders made 26.5% of their loans to Black-owned firms. CDFIs' large share of lending to Black-owned businesses is consistent with their mission to provide financial services to economically disadvantaged individuals within underserved communities. The reasons for the large share of lending to Black-owned businesses by fintech lenders are not immediately obvious as they do not, in general, have a mission to serve a particular racial or ethnic group more than others. Appendix Table A.1 shows that while there is some variation across fintech lenders in the share of PPP loans to Black-owned firms, this disparity is not driven by a few lenders.

Panel B of Figure 1 shows the share of all loans to Black-owned businesses by lender type (see also Panel A of Table 3). Fintech lenders were responsible for 53.6% of PPP loans to Black-owned businesses in our sample. We find similar results using only PPP loans with self-reported data on owner race (see Appendix Figure A.2). We present the same figures for the other three racial and ethnic groups in our data in Appendix Figures A.3-A.5. Key summary statistics for all the racial and ethnic groups are in Table 3. Black-owned businesses exhibit by far the most striking disparity across lender types, especially their propensity to obtain PPP loans from fintech firms instead of other lenders. The primary objective of the rest of the paper is to assess a variety of plausible mechanisms for the observed disparities across lender types in lending to Black-owned businesses.

2.1 Observable Loan and Borrower Characteristics

While the higher share of PPP loans to Black-owned businesses by fintech lenders is striking, it may reflect the unique characteristics of those businesses. Black-owned firms receive the smallest PPP loans, with a mean amount of $24,315, compared to about $54,000 for Hispanic- and Asian-owned firms, and $110,317 for White-owned firms (Panel A of Table 3). Similarly, while 63.4% of all businesses obtaining PPP loans are employer businesses, only 21.0% of Black-owned businesses obtaining PPP loans are employers. These characteristics, in particular the differences by loan size, could explain some of the differential lending rates. As Section 1 explains, lenders were compensated for originating PPP loans with a fixed fraction of the loan amount. In the presence of fixed costs or capacity constraints, this would incentivize lenders to first process the largest loans, which were disproportionately given to non-minority-owned businesses. If capacity constraints or fixed costs were smallest among fintech lenders (and largest among small banks), this could explain some of the differential lending rates across bank types to Black-owned businesses.

In the next step, we explore the propensity for Black-owned businesses to obtain their PPP loans from fintech or other lenders in a multivariate regression framework represented by Equation 1:

$$\mathbb{1}(\text{BankType}_i) = \beta\mathbb{1}(\text{BlackOwned}_i) + \mathbf{X}_i\delta + \varepsilon_i. \tag{1}$$

The dependent variable, $BankType_i$, is an indicator for whether a PPP borrower gets their loan from a certain type of lender. The key explanatory variable is an indicator for whether a firm is Black-owned, as defined in the previous section. For example, when $BankType_i = Fintech_i$, the coefficient β measures the higher propensity (in percentage points) for Black-owned businesses of obtaining a PPP loan from a fintech lender. The vector $\mathbf{X}_i$ captures control variables that vary across specifications.

Unconditionally (i.e., with no controls), we find that Black-owned businesses were 39.7 percentage points more likely to obtain their PPP loan from a fintech lender (Column 1 of Panel A of Table 4). In column 2, we include fixed effects for each percentile for the loan size distribution. Despite Black-owned PPP borrowers having much smaller loans on average, controlling for loan amount explains only a modest part of the disparity. Conditional on loan size, Black-owned businesses remain 31.6 percentage points more likely to borrow from a fintech lender.

As many traditional lenders focus their operations on certain parts of the country and the Black population is not evenly distributed (see Appendix Figure A.6), we also consider the possible role of firm location in explaining the observed lending patterns.[13] In column 3, we include firm zip code fixed effects, and in column 4, we include firm census tract fixed effects. Including controls for the location of the business has a sizable effect on the R^2 of the regression. It also reduces the excess probability that Black-owned businesses obtain PPP loans from fintech lenders to 23.2 percentage points (in the model with zip code fixed effects), consistent with traditional lenders lending less in locations with more minority-owned businesses (see Erel and Liebersohn, 2020). Indeed, in Appendix Table A.6, we verify that all businesses located in areas with high minority ownership—even businesses in those areas that are owned by White individuals—were somewhat more likely to obtain their PPP loans through fintech lenders. An important question for future research is thus why traditional lenders are less likely to serve people (of any race) in high-minority neighborhoods. This finding could, for example, be explained if conventional lenders chose to locate fewer bank branches in high-minority neighborhoods, leading them to process fewer PPP applications from local businesses in these areas. Overall, however, it appears that lenders' geographic focus can explain some, but not all (and not even the majority) of the racial gap in

[13]While differently-sized loans have differential profitability to lenders, other characteristics, such as firm location, should not affect the profitability of extending the federally-guaranteed PPP loans.

the propensity to borrow from different types of lenders.

In the next step, we explore the role of the timing of the PPP application. Initially, only a few fintech lenders were approved to participate in the program, with the rest entering in the subsequent months. If Black-owned businesses were more likely to obtain their PPP loans later in the program, then this may have led to a natural relationship between race and the propensity to obtain PPP loans through a fintech lender. Indeed, Figure 2 shows how the share of PPP loans made to Black-owned businesses (Panel A) and the share of PPP loans made by fintech lenders (Panel B) both increased over time (see also Appendix Table A.7). These patterns could either reflect a coincidence, whereby Black-owned businesses may have only learned about and applied for the program in later periods when more fintech lenders were included, or a causal relationship, whereby the absence of fintech lenders in the early stages of the program are part of the reason why Black applicants struggled to obtain PPP loans during that period. After additionally including "week of approval" fixed effects, the estimated β-coefficient remains at an economically large 17.5 percentage points.[14] Therefore, a coincidence in timing cannot explain the majority of the disparity.

In columns 6 to 8 of Panel A of Table 4, we explore the role of industry, business type, and employer status.[15] Importantly, column 7 includes zip-by-industry interacted fixed effects, in case lenders perceive certain industries in certain areas differently. In our most richly controlled model, the unexplained excess share of loans to Black-owned businesses by fintech lenders is 12.1 percentage points (column 8). This represents 70% of the mean chance of a fintech loan (throughout the paper, we report the mean of the dependent variable towards the bottom of the table).[16]

In sum, fintech lenders made a substantially larger share of their loans to Black-owned businesses than traditional lenders did, a disparity that does not appear with similar magnitude for other racial or ethnic groups. Controlling for a rich set of observable loan and borrower characteristics can jointly explain 69% of the higher chance that Black-owned businesses borrow from fintech lenders ($.69 = \frac{.397-.121}{.397}$). Since many of the firm characteristics are correlated, it is challenging to attribute a relative importance to each of these factors, and changing the order in which we include these controls in Table 4 changes their relative contribution to reducing the estimate of β. The key point for our analysis, however, is that 31% of the gap remains unexplained, even in models that hold the profitability and timing of lending and the location and characteristics of the firm fixed. Exploring possible explanations for this remaining gap is the central contribution of our paper.

[14] In Appendix Table A.8, we estimate Equation 1 separately for loans approved in each of the four phases of the PPP program. This is also shown in Appendix Figure A.7. The main takeaway from Table 4 is consistent across rounds: fintech lenders made a much larger share of their loans to Black-owned businesses compared to traditional lenders.

[15] Borrower industry is captured with NAICS 3-digit industry fixed effects. Examples of industries in this classification scheme are "Health and Personal Care Stores," "Truck Transportation," and "Food Services and Drinking Places." Table 3 Panel A shows that business type and industry distribution differ by owner race. For instance, Black-owned businesses are substantially more likely to be self-employed or sole proprietorships and less likely to be corporations or LLCs.

[16] Appendix Table A.9 repeats this exercise but restricts to the sample of employer firms only. Although the magnitude of the coefficients decreases somewhat, they remain robust and are larger relative to the mean chances of a fintech loan. With our full set of controls in column 8, Black-owned employer firms are 7.5 percentage points more likely to get a fintech loan, which is 77% of the mean. We repeat these models using self-reported race in Panel A of Appendix Table A.12. The sample is restricted to the subset of roughly one million loans for which race/ethnicity is reported in the SBA data. In this smaller and selected sample, the results are quite similar to the main findings, though the magnitudes are somewhat larger.

Across-Bank Heterogeneity. Given that Black-owned businesses are more likely to get their PPP loans from fintech lenders, which types of lenders does this substitution come from? We explore this question in Panel B of Table 4, where we replace $BankType_i$ in Equation 1 with an indicator for obtaining the PPP loan from a Top-4 bank (Bank of America, Wells Fargo, Citi, JP Morgan), a large bank, or a small/medium bank. Unconditionally, Black-owned businesses were less likely to get their loans from all of these types of banks, consistent with the findings in Table 2. However, after including controls, this relationship is near-zero for the Top-4 banks, and the majority of the 12.1 percentage point fintech disparity in column 8 of Panel A of Table 4 is accounted for by lower rates of small/medium bank PPP lending to Black-owned businesses. Unconditionally, Black-owned businesses were 30 percentage points less likely to get their PPP loans from a small bank (column 5); in the model with full controls (column 6), this gaps remains an economically large 8.1 percentage points.[17,18] The results using self-reported race in Appendix Table A.12 Panel B are similar.

The heterogeneity across different conventional banks helps assess the potential role of compliance with Know-Your-Customer and Anti-Money-Laundering (KYC/AML) regulations in explaining the differential lending to Black-owned businesses. The Top-4 banks, as international institutions with charters in all or most U.S. states, are the most tightly regulated banks (Congress, 2009). Consequently, the fact that, conditional on controls, the most-regulated and least-regulated entities in our sample—the Top-4 banks and the fintech lenders—had the highest probability of granting PPP loans to Black-owned businesses makes differential compliance standards an unlikely explanation.[19]

We are also interested in understanding whether small banks' low rates of lending to Black-owned businesses reflect higher rates of lending to all other races or to one race in particular. Panel C of Table 4 includes indicators for the three other races and ethnicities as explanatory variables. Since the four racial and ethnic groups span the data, the coefficients should be interpreted as the probability of obtaining a PPP loan from a particular lender type relative to the probability for Black-owned businesses. After including controls, there is zero difference between Black- and White-owned businesses in the chances of getting a PPP loan from a Top-4 bank (column 4), while Asian- and Hispanic-owned businesses were marginally more likely to get their PPP loan from a Top-4 bank. In contrast, on a percentage point basis, small- and medium-sized banks lent particularly more to White-owned businesses (columns 7-8). For example, unconditionally, White-owned businesses are 35 percentage points more likely than Black-owned businesses to get their PPP loans from smaller banks (column 7). With controls, this gap remains

[17] Note, however, that the 2.5 percentage points effect identified for non-Top-4 large banks corresponds to a larger share of their unconditional mean probability of originating any loan, at 26%, than the 8.1 percentage points effect at medium and small banks, at 17% of the mean.

[18] We visualize the across-lender patterns by comparing all 11 types of lending institutions simultaneously in Figure 3. Here, we show the degree to which the lender types were statistically different from one another in their propensity to lend to each of the four racial and ethnic groups, conditional on our rich array of controls. The fraction of fintechs' loans to Black-owned businesses was over five percentage points higher than the fraction for other lender types. MDIs made a disproportionate share of their loans to Asian-owned businesses. Note that the reversal for MDIs in Hispanic loans relative to the summary statistics reflects the location control; in particular, a very large MDI in Puerto Rico.

[19] To underline this cross-bank heterogeneity independent of fintech loans, Appendix Table A.10 Panel A repeats Panel B of Table 4 but excludes fintech loans. The results show that relative to all remaining lenders, Top-4 banks are significantly more likely to lend to Black-owned businesses (columns 3-4) while smaller banks are much less likely to do so (columns 7-8).

an economically large 10 percentage points, and we continue to find similar results using self-reported race (Appendix Table A.12 Panel C) or excluding fintech loans (Appendix Table A.10 Panel B).

Strength of Algorithm's Race Signal. In our baseline analysis, we assign every individual the race with the highest probability from our machine learning algorithm. We next explore whether, among individuals predicted to be Black, the strength of the race signal correlates with variation in PPP lender type. Specifically, we divide all individuals predicted to be Black into five quintiles based on the algorithm's predicted probability that they are Black (see Section 1.2 for the full distribution of this probability). Individuals in the 5th quintile deliver the strongest signal that they are Black to lenders given their name and location.[20]

Table 5 shows that the magnitude of our main results increases monotonically with the signal strength. As in Panels A and B of Table 4, the omitted group is all borrowers not predicted to be Black. Panel A shows that across the quintiles of increasing probability that the business owner is Black, the chance of having a fintech loan increases. In the fully controlled model in column 8, Black-owned businesses in the first quintile are only 4.3 percentage points more likely than other groups to have a fintech loan. In the third quintile, they are 12.7 percentage points more likely, and in the fifth quintile, they are 24.7 percentage points more likely. Similarly, Panel B explores the probability of obtaining loans from conventional lenders, again with the most striking differences among small- and medium-sized banks (columns 5-6). Conditional on controls, borrowers in the first quintile are 3.1 percentage points less likely to get a small/medium bank loan, while those in the fifth quintile are 15.2 percentage points less likely to do so. In sum, these results help to validate the algorithm and point to a potentially important role for the degree of "Blackness" as suggested by the audit literature (Bertrand and Mullainathan, 2004).

2.2 Borrower Bank Relationships and Financial Situation

In this section, we explore the importance of two channels that may help explain why the propensity of Black-owned businesses to obtain PPP loans varies across lender types: differences in pre-existing banking and credit relationships, and differences in firm financial health.

Pre-existing Banking Relationships. A number of observers of the PPP program have highlighted that many banks tended to first serve their own clients' PPP loan applications, which may have distorted allocations away from the government's intended "first come, first serve" approach (Cowley, 2021; Rosenberg and Myers, 2020; Li and Strahan, 2020).[21] If banks indeed prioritized administering PPP

[20] In the self-reported data, individuals in the 3rd, 4th, and 5th quintiles of probability Black have more than a 99% chance of self-identifying as Black (recall that these quintiles are calculated within the population for whom Black has the highest probability across the races). The 1st quintile individuals have a 78% chance of being Black, and the 2nd quintile individuals have a 97% chance.

[21] There are a number of explanations for prioritizing PPP applications from existing customers. First, it may have been cheaper to process these applications. Second, this might be optimal for banks if receiving a PPP loan increases the chances that a borrower repays existing loans, including possible loans to the PPP lender (Granja et al., 2020). Third, even in the absence of

loan applications from their own clients, and if Black-owned businesses did not bank with active PPP lenders, this could explain some of the observed differences in their propensity to eventually borrow from other lenders such as fintech firms.

To quantify the effect of pre-existing banking relationships, we turn to the sample of PPP borrowers matched to bank statement data. Indeed, we find that conventional banks' PPP clients were also often their business checking account clients. Panel C of Table 1 shows that 28.5% of PPP borrowers had a checking account at their PPP lender; of the PPP loans originated by large banks and the Top-4 banks, more than 50% went to existing checking account customers. For fintech lenders, which do not usually offer checking accounts, this number was essentially zero.[22]

Although conventional lenders served their own clients at higher rates, we show in Table 6 that this fact does not explain the higher rate of fintech PPP loans for Black-owned businesses. First, we estimate the fully controlled model from Table 4, Panel A, column 8, in the bank statement-matched sample. Here, Black-owned businesses are 5.5 percentage points more likely to obtain their PPP loan from a fintech lender (column 1). Selection into having a checking account could help explain the smaller effect size; that is, the larger gap in the full sample could reflect Black-owned businesses being less likely to have *any* banking relationships, and therefore less likely to have a "house bank" prioritizing their PPP loan application. However, we do not find this explanation compelling. This story would suggest that Black-owned firms should be a smaller share of the bank statement-matched sample than the full sample, because the former obviously requires the firm to have a checking account. As shown in Panels A and B of Table 2, this is not the case; in fact, Black-owned firms even represent a somewhat larger share of the bank statement-matched sample. Instead, we believe that the somewhat smaller magnitude of the baseline effect in the bank statement-matched sample likely reflects a higher rate of clients with fintech affinity, which would raise the share of fintech PPP loans among borrowers of all races and ethnicities.

In Column 2 of Table 6, we add fixed effects for the identity of the bank where the firm has a checking account. In this model, we are comparing, for example, the origination of PPP loans to Black-owned firms and other firms with a checking account at JP Morgan Chase. The inclusion of these fixed effects has essentially no effect on the estimated probability of Black-owned businesses to obtain their PPP loans from fintech firms. Therefore, the observed racial difference in this probability is not driven by Black-owned firms holding their checking accounts at banks that were less active as PPP lenders.

We next assess whether, after controlling for observable characteristics, there are racial differences in the propensity of a firm to obtain its PPP loan from its checking account bank. On average, Black-owned businesses were between 1.1 and 1.7 percentage points less likely to obtain their PPP loans from their checking account banks (Table 6, Panel B, columns 7-8).[23] In Table 7, we split the sample of checking

an existing credit relationship between banks and their clients, banks might prioritize existing clients if they perceived a positive net present value from the relationships, and receiving a PPP loan would improve the chances of those clients surviving.

[22]Table 3 Panel B shows that within the bank statement-matched sample, Black-owned businesses are the most likely, at 17.2%, to have their checking account with a lender that is not a traditional bank. Black-owned businesses have similar or slightly higher chances of having a credit relationship with another non-fintech lender in this sample, though this could reflect business credit cards which represent a more arms-length relationship than traditional small business loans.

[23]Anecdotes from the popular press offer examples of Black-owned businesses failing to obtain PPP loans through their

account holders by the identity of the checking account bank. Among firms with checking accounts at Top-4 banks (Panel A), we find no differential probability of Black-owned businesses to obtain their PPP loans from their checking account bank. The negative coefficient in the full sample stems from large banks (Panel B), with a smaller relationship for smaller banks (Panel C).

In columns 2-5 of Table 7, we show that Black-owned firms' differential chance of getting a fintech loan versus a non-Top-4 bank loan is similarly large regardless of where they have their checking account, and exists even for borrowers with checking accounts at Top-4 banks. This difference is largely explained by variation in the identity of the PPP lender among those firms that do not obtain their PPP loan from their checking account bank.

Overall, these findings highlight two channels that made it more likely for Black-owned businesses to obtain their PPP loans from fintech lenders. First, Black-owned firms with checking accounts at non-Top-4 banks were somewhat less likely to obtain their PPP loans from their checking account bank. Second, among firms that obtained PPP loans outside their checking account banks (which includes both Black-owned and non-Black-owned firms), Black-owned firms were much less likely to obtain loans from non-Top-4 banks, and much more likely to obtain them from fintech lenders. Quantitatively, this second channel, which captures racial differences in the rates of establishing new banking relationships with different types of lenders, explains the majority of the observed disparity.

Pre-existing Credit Relationships. We next explore the possible role of prior credit relationships in explaining the observed differences in PPP lending outcomes. Specifically, in column 3 of Panel A of Table 6, we include indicators for whether a PPP borrower has credit relationships with any fintech and conventional lenders. Unsurprisingly, a prior credit relationship with a fintech lender is associated with a significantly higher chance of obtaining a PPP loan from a fintech lender. At the same time, columns 2, 4, and 6 of Panel B show that such a prior relationship reduces the likelihood of getting a loan from all types of traditional banks. Similarly, having previously received credit from a non-fintech lender reduces the likelihood of getting a fintech PPP loan and increases the probability of a non-fintech PPP loan.

The preferential treatment of firms with prior credit relationships, however, does not account for the disproportionate lending to Black-owned businesses by fintech lenders in the PPP program: Black-owned businesses are 5.6 percentage points more likely to get their PPP loan from a fintech lender compared to other PPP borrowers, even after conditioning on the identity of the checking account bank and the presence of credit relationships with both fintech and non-fintech lenders (column 3 of Table 6). This is largely because, within the bank statement-matched sample, there are no substantial differences across races in having various credit relationships (see Table 3, Panel B).

checking account banks. For example, the Associated Press interviewed Lisa Marsh, who is Black and the owner of MsPsGFree, a Chicago-based gluten-free baking business (Rosenberg and Myers, 2020): "Lisa Marsh tried in vain to get banks to process her application. She first applied in June but she couldn't get answers on her status from her bank, a subsidiary of a big national bank. She also got nowhere with smaller community banks... [Marsh] finally applied through an online lender in late July and got her loan a few days before the PPP ended. "I was very frustrated and almost gave up," she says." In a similar story, the New York Times described Black auto dealership owner Jenell Ross who, "sought a Paycheck Protection Program loan, [but] her longtime bank told her to look elsewhere" (Cowley, 2021). In the absence of formal statistical analysis like the one we provide, it is obviously impossible to say whether such challenges were disproportionately encountered by Black-owned businesses.

Firm Financial Health. We next explore whether the differential financial performance of minority-owned firms can explain the remaining observed racial disparities in PPP lending. Recall that PPP lenders were not responsible for any loan losses; therefore, creditworthiness should be irrelevant to the one-shot decision of making a PPP loan. However, lenders may nonetheless have been more likely to lend to businesses in better financial positions, for example, because they might represent more attractive future customers. There could also be some stickiness in the behavior of loan officers who are used to screening for creditworthiness, causing them to screen on financial signals as they do in their usual course of business.

Panel B of Table 3 shows that gross and net inflows at Black-owned businesses are, at the median, less than half of their values for the other racial groups. To assess whether these differences affect our results after conditioning on firm size, we first add granular controls for a firm's gross and net cash inflows from the most recent bank statement in column 4 of Panel A of Table 6. Black-owned businesses remain 5.5 percentage points more likely to receive a fintech loan, suggesting that the cash-flow situation of borrowers does not explain the observed racial differences in the identity of the PPP lender.[24]

We also assess whether differences in contemporaneous revenue explain the observed disparity. If lenders treated Black-owned firms differently because they were doing relatively poorly during the pandemic, controlling for revenue during this period should eliminate the disparity. Our data on credit and debit card spending from Enigma allows us to observe the firm over the course of the COVID-19 economic crisis and PPP loan application period. We use these data to control for revenue around the time of application. We show results using the card revenue-matched sample in Table 8. We continue to include all controls available in the PPP data.

Given the sample differences highlighted in Section 1.4, we first re-estimate the main model to establish a baseline. Column 1 of Table 8 shows that, in this sample, Black-owned firms are 1.6 percentage points more likely to get a fintech PPP loan—this effect corresponds to about 17% of the mean probability. In this sample, Black-owned firms are slightly more likely to get their PPP loans from Top-4 banks (columns 3-4), and substantially less likely to get PPP loans from small- and medium-sized banks (columns 7-8). Importantly, adding fixed effects for 100 equal-sized groups of credit card revenue has no effect on these racial disparities, consistent with our findings when we controlled for cash flows observed in the bank statement data. This pattern continues to hold when we measure revenue only in the approval month (Appendix Table A.14).[25] Hence, while the Enigma sample generally includes larger and more consumer-oriented firms among which Black-owned businesses appear to be at less of a disadvantage, we find no evidence that real-time revenue differences help explain the main findings.

[24] We repeat Table 6 with indicators for whether a business is Asian-, Hispanic-, and White-owned in Appendix Table A.11. We continue to find similar results. For example, these regressions show that, after controlling for bank and credit relationships as well as cash flows, small banks are significantly more likely than other non-fintech lenders to serve White-owned businesses.

[25] In Panel B of Table 8, we restrict the sample to firms that appear especially harmed by the COVID-19 economic crisis. These are firms for which we observe monthly revenue in February 2020 but not in the approval month. Note that we do not observe revenue if there are fewer than 30 transactions. Therefore, these "struggling" firms have either no activity or limited activity relative to February. We repeat our main models from Table 4 within this sample of "struggling" firms. In the model with full controls, and among this sample of struggling firms, Black-owned firms are 2.1 percentage points more likely to get their PPP loan from a fintech firm.

3 Borrower Application Behavior

Our primary data includes only originated loans and does not contain information on loan applications. This leaves open the possibility that the differential rate at which Black-owned businesses end up borrowing from different types of lenders is the result of their application behavior. In this section, we therefore explore whether the observed equilibrium lending outcomes might in part be explained by Black-owned businesses being more likely to apply to fintech lenders than to non-Top-4 banks.

3.1 Differential Fintech Affinity.

One reason Black-owned businesses may have been more likely to apply to fintech firms is that they may have been more tech-savvy or have had higher fintech affinity.[26] To test this hypothesis, in Panel D of Table 7, we condition on firms in the bank statement-matched data that we observe having a pre-existing credit relationship with fintech firms. Within this sample of firms, all of which have shown a certain degree of past fintech affinity, we continue to find an economically important substitution of PPP borrowing of Black-owned businesses from small and medium banks towards fintech lenders. This finding reduces the likelihood that the results are driven by an increased fintech affinity of Black-owned businesses.

3.2 Analysis within PPP Application Data from Lendio.

For some borrowers who applied for a PPP loan through Lendio, a marketplace platform for small business loans, we have information on the set of lenders to which Lendio forwarded the application. Lendio is a platform through which businesses could submit PPP applications, which were then forwarded to around 300 partner lenders. Some of these Lendio partner lenders were fintech firms, and some were conventional banks. Our conversations with Lendio executives, including CEO Brock Blake, suggest that the routing of the applications to lenders was random conditional on loan size, geography, and capacity criteria set by the lender partners. Banks then had the opportunity to follow up with the applicant firms to complete the application (firms also retained the option to apply for a PPP loan through other lenders). In these data, we can assess whether Black-owned businesses remain more likely to ultimately get a fintech loan conditional on the types of banks Lendio forwards these loans to.

We obtained data on all PPP loan applications through Lendio up until November 2020. The data include applications from about 267,000 firms, about 176,000 of which we can link to final PPP loans in our data. The remaining applicants either never got a PPP loan, or we were unable to match them to firms in the main dataset. In our analysis, we focus on the sample that ultimately received PPP loans since this is the sample for which we can generate our name-based race proxy. We divide the lenders who

[26] A different possibility within the scope of application behavior is that because Black communities were disproportionally affected by COVID-19, and because banks are more associated with in-person interaction than fintechs, Black business owners were more likely to apply to fintechs in order to avoid in-person interaction. In unreported analysis, we find that COVID-19 prevalence cannot explain the main finding. Even in areas with low COVID-19 cases and deaths, Black-owned businesses were substantially more likely to receive fintech PPP loans.

ultimately originated the loans into two groups: fintech and conventional lenders (where conventional includes all other lender types). The main sample characteristics according to this split are summarized in Panel C of Table 2. About half the PPP loans to firms that applied through Lendio were originated by fintech lenders, a result that is unsurprising given that Lendio is an online platform. The share of Black borrowers across conventional and fintech lenders, as well as the average difference in loan size, however, is quite similar to the main samples. Panel C of Table 3 shows that the average application was routed to 1.5 lenders, of which 0.9 were fintechs and 0.6 were conventional lenders.

In Table 9, we again present results from Equation 1. As before, we begin by establishing a baseline by replicating the result from column 8 of Panel A of Table 4 within the Lendio sample. Column 1 of Table 9 shows that, conditional on our controls, Black-owned businesses in this sample were 2.9 percentage points more likely to obtain their PPP loan from a fintech lender. The somewhat smaller disparity compared to our baseline estimate likely reflects the composition of lenders that Lendio partners with. To show this, column 2 explores a sample of PPP loans originated by Lendio partners, but to firms that did not apply through Lendio (thereby removing any effects that might occur due to firm selection into the Lendio data). The coefficient of 2.6 percentage points is very similar to the previous column, indicating that the smaller baseline disparity likely reflects lender composition.

Next, in column 3, we add interacted fixed effects for the number of lenders to which Lendio routed the application in both the fintech and conventional categories. The disparity remains at 2.8 percentage points, suggesting that differential application behavior by Black-owned businesses has at most a small role in explaining the lending patterns by race documented in this paper. Instead, this result points to lender decision-making playing a role. In Column 4, we restrict the sample to loan applications that were sent to at least one conventional lender, while Column 5 focuses on applications that were sent only to conventional lenders. Both specifications control for the number of lenders the application was sent to in each category. These models continue to find that Black-owned businesses were more likely to ultimately have a fintech loan. For example, the estimate in column 5 suggests that Black-owned businesses are 3.9 percentage points (36% of the mean) more likely to get a fintech loan than non-Black-owned businesses, *even* when Lendio only sent their application to conventional lenders. These Black-owned firms obtained fintech PPP loans outside of Lendio. Overall, our results in this section suggest that racial differences in the probability of applying to conventional lenders versus fintech lenders cannot explain our findings and that, instead, different behavior across lender types is likely to explain why Black-owned businesses receive fintech loans at substantially higher rates.

3.3 Differential Fraud Rates.

A remaining possibility related to borrower behavior is that our results might reflect statistical discrimination based on differential fraud rates. If Black business owners were *much* more likely to submit fraudulent PPP applications and fintechs had *much* lower compliance standards, in particular relative to small banks, this channel could contribute to the large observed disparities. Consistent with the second part of this proposition, PPP loans by fintechs have indeed been identified in Griffin et al.

(2021) as having a higher rate of fraud.

We directly assess this possibility using unsealed PPP fraud cases prosecuted by the U.S. Department of Justice as of November 15, 2021.[27] We match the companies named in the affidavits to borrowers in our PPP loan sample (from Table 1 Panel B), and are able to identify 268 matched cases, out of which 191 have a race prediction. Appendix Table A.18 shows that the share of cases in this sample where the company is Black-owned is 8.4%, which is almost exactly the Black-owned share of the overall sample of 8.6% (Table 2 Panel A). Therefore, if small banks statistically discriminated against Blacks on this basis, they were incorrect.[28] Beyond this analysis, we believe that a differential fraud channel to explain our main findings is implausible for two reasons. First, as explained in Section 1, the CARES Act effectively indemnifies lenders against liability for borrower fraud if the lender is unaware. To our knowledge, no case has been brought to date against a lending institution. Second, we would not expect the effect to be driven by small banks, because top banks are the most tightly regulated and have the most advanced compliance systems.

4 Discrimination: The Role of Racial Animus and Automation

In this final section, we explore whether preference-based discrimination may contribute to explaining some of the remaining disparity between fintechs and smaller conventional lenders in their propensity to provide PPP loans to Black-owned businesses. This channel would involve potential biases among loan officers during the manual review and processing of PPP applications. Such manual involvement of loan officers was relatively common among conventional lenders, especially among smaller and medium-sized banks. For example, one industry article profiled the approach of The Piedmont Bank in Georgia, a small SBA-preferred lender:

> "While The Piedmont Bank considered some automated, online solutions, they ultimately decide to process the applications manually...Everyone who works there is preparing to put in long hours and a lot of elbow grease. They know they're going up against big banks and their automated systems." (Smith, 2020)

As a second example, an industry article mentions that:

> "In the initial round of the Paycheck Protection Program, First Bank in Hamilton, N.J., leaned on its bankers rather than technology to help small businesses stay afloat. That manual labor "ironically turned out to be a good thing, because we had people helping small businesses through the process, and they had a number and name to talk to," said Patrick Ryan, president and CEO of the $2.3 billion-asset bank." (Cross, 2021)[29]

[27] We gather cases from the DOJ website as well as the law firm Arnold & Porter's website. These are available here and here.

[28] We also report the share of these loans originated by small banks, top banks, and fintechs. We see that fintechs originated a large share, at 46%. This is consistent with Griffin et al. (2021), whose analysis implies about 60% of fraudulent loans are made by fintechs (based on their Table 3).

[29] As a third example, RCB Bank of Oklahoma and Kansas did not even allow borrowers to apply online for PPP loan

When reviewing PPP loan applications, loan officers may become aware of applicant race through a number of channels. One is visually through manual review of driver's licenses, which were required (in color) for all PPP applicants. A second channel is through information such as the applicant's name, which we have shown to be highly predictive of race.[30]

If preference-based discrimination contributed to the observed higher probability of otherwise similar Black-owned businesses obtaining a PPP loan through a fintech lender rather than a non-Top-4 bank, we would expect this gap to be larger in regions with higher racial animus. We next explore this hypothesis and find that Black-owned businesses were indeed more likely to get their PPP loans from fintech lenders (and less likely to get them from small- or medium-sized banks) in regions with higher racial animus. We also study the lending behavior of small banks that automated their lending processes during our sample period, and explore whether following the automation, there were significant changes in their lending to Black-owned businesses.

4.1 Racial Animus Data.

We collect six measures of anti-Black racial animus at the local level. The first measure comes from Stephens-Davidowitz (2013) and is calculated at the level of the designated media market. It measures the percentage of an area's Google searches that contain racially charged words. The second measure follows Bursztyn et al. (2021) and is based on how favorably White respondents rate Black Americans as a group in the Nationscape survey; individual responses are aggregated up to the congressional district level (Tausanovitch and Vavreck, 2020). The third measure of racial animus is based on the Implicit Association Test (IAT), which measures implicit bias against Black individuals. The fourth measure is based on a survey question that explicitly asks individuals who just took the IAT for their feelings towards Black Americans. These IAT-based measures are aggregated up to the county-level (Xu et al., 2014). The last two measures of racial animus are based on the extent of local residential segregation (Massey and Denton, 1988). The first of these, the dissimilarity index, measures how similar the distribution of White and Black residents are across city tracts. The second is the isolation index, which measures the probability of a Black resident sharing the same city tract with another Black resident. The segregation measures are available at the metro/micropolitan statistical area (MSA) level. Appendix A describes these measures of racial animus in more detail, and examines their geographic variation and the degree to which they are correlated with one another. Importantly, Appendix Figure A.9 shows that the places where racial animus is high differ substantially across our measures, indicating that they offer somewhat independent signals of animus.

forgiveness, but instead stated that "A Loan Officer will contact you to discuss your forgiveness eligibility and provide you with the appropriate loan application via DocuSign" (see RCB Bank Example). As a fourth example, Skip advised customers that "While many lenders spent the time to automate processes and increase their throughput, many have not and may be doing manual review" (see Skip Example).

[30] Most Americans can infer race for a large fraction of names, perhaps not with the accuracy of our algorithm, but well enough to lead to systematic bias (Bertrand and Mullainathan, 2004; Milkman et al., 2012; Bartoš et al., 2016).

4.2 Differential Effects by Racial Animus.

Table 10 estimates whether, for a Black-owned firm, the probability of obtaining a PPP loan from different lenders varies with the degree of racial animus in the firm's location. In Panels A, B, and C, the dependent variables are indicators for obtaining a PPP loan from a fintech, a Top-4 bank, and a non-Top-4 bank, respectively. In each panel, column 1 includes the same controls as the specification in column 8 of Panel A, Table 4. In columns 2-7, we interact our indicator for Black-owned businesses with each of the proxies for racial animus. The location fixed effects absorb any direct effect of racial animus on the probability of borrowing from fintech lenders that is constant across all borrowers. Each measure of racial animus is standardized to have a mean of zero and a standard deviation of one, so the coefficients can be interpreted as the effect, in percentage points, of a one standard deviation increase in the racial animus measure.

In Panel A of Table 10, we consider the effects of increased racial animus on the probability of a Black-owned firm obtaining a PPP loan from a fintech lender. We find a robust positive interaction between the various racial animus measures and Black ownership. The coefficient magnitudes vary from 0.4 to 2.9 percentage points. This implies that, relative to the mean chances of a fintech loan of 17.4%, a one standard deviation increase in racial animus is associated with a 2.3% to 17% increase in the probability that a Black-owned business obtains their PPP loan from a fintech lender. With the implicit bias (IAT) measure—which is probably the most widely used in the academic literature—the coefficient estimate of 1.3 percentage points implies a 7.5% increase. In sum, while the magnitude of the relationship varies somewhat across measures, we find robust evidence that in areas with higher racial animus, Black-owned businesses are more likely to obtain their PPP loans from fintech lenders.

We repeat this exercise for the Top-4 banks in Panel B. Here we see near-zero coefficients on the interaction, which flip signs across the animus measures. This is consistent with our previous analysis finding no racial differences in the conditional probability of obtaining a PPP loan from a Top-4 bank. In contrast, we estimate a robust negative interaction term for non-Top-4 banks in Panel C, suggesting that higher racial animus makes Black-owned firms less likely to receive their PPP loans from those non-Top-4 banks. The coefficient using the implicit bias (IAT) measure of -2.4 percentage points implies that a one-standard-deviation higher racial animus score is associated with a 4.2% decrease in the probability of Black-owned businesses obtaining their PPP loans from non-Top-4 lenders. In Appendix Table A.15, we repeat these three panels within the bank statement-matched sample and find similar results, even after controlling for the identity of the checking account bank and firm financial performance.

4.3 Automation as a Mechanism.

A number of our previous results suggest that the degree of automation in the lending process may help explain some of the disparities in the propensity to serve Black-owned businesses. First, fintechs, which have automated processes at the core of their business models, made a disproportionately large share of their loans to Black-owned businesses. Second, among conventional lenders, smaller banks account for most of the lower rate of PPP lending to Black-owned businesses, particularly in models that control for observable borrower characteristics. In contrast, after including controls, we find no such differences in the probability of borrowing from Top-4 banks. While we do not have systematic data on the degree of automation by bank, automation is widely believed to increase in bank size and to be particularly widespread at the very largest banks. Survey and anecdotal evidence support this narrative. One industry article notes that "Large banks have avidly adopted robotic process automation . . . It's tougher for smaller banks to follow suit" (Crosman, 2020). A 2018 Fannie Mae survey found that 76% of large banks but only 47% of small banks were familiar with artificial intelligence or machine learning technology. At smaller banks, humans—with all their biases—generally play a larger role in the loan origination process. As a colorful example, Cross (2021) explains:

> "In community banking, when you're closing a loan, you're probably closing it with a lady or gent you went to high school with, maybe on the hood of a Cadillac at a Friday night football game or Sunday after church. Those things are nice, but they don't scale."

In this last section, we further study the effect of automation by exploiting the fact that, during the PPP loan period, a number of small banks automated their loan origination processes, many of them by collaborating with fintech software providers such as Numerated and Biz2Credit. For example, one bank official attested that: "Compared to 10 days of manual lending, with every bank resource that we had, in terms of volume of new loans generated, we were able to do it in 2 days with [Numerated]." As a second example, Cross (2021) explains that:

> "When HV Bancorp in Doylestown, Pennsylvania, first went live with the Paycheck Protection Program last April, "we just had bodies in front of keyboards using the Small Business Administration's E-Tran system and entering applications," said Hugh Connelly, chief lending officer in the business banking division of Huntingdon Valley Bank...The urgency of the Paycheck Protection Program propelled community banks to find a speedier way to disburse loans to small businesses than relying on phone and email. Many turned to software to originate loans, automate the underwriting process, collect documents and transmit the information to the SBA's processing system."

Our formal analysis of the effects of automation on lending patterns proceeds in two steps. We first identify a set of small banks that automated their lending processes during the PPP period. We then show that their rate of lending to Black-owned businesses increased disproportionately following the automation compared with other small banks that did not automate their lending processes.

Data. We gather data from the fintech firm Biz2Credit on small banks that—motivated by the influx of PPP loan applications—hired Biz2Credit to automate lending during the second round of the PPP. Biz2Credit offers a white label SaaS product called Biz2X that banks can license to outsource and automate their loan processing and underwriting. Once a bank automates using Biz2X, loan application materials are automatically redirected from the bank's website to Biz2Credit. Biz2Credit then conducts fraud checks and ensures compliance with PPP eligibility rules, makes a decision, and forwards the required materials back to the bank to originate the loan.[31] Biz2Credit provided us with the launch date of their service for their clients during the PPP. We matched these clients to our list of banks in the SBA data. We also manually searched newspaper articles to identify additional automating small banks. The banks that are not Biz2Credit clients automated via a range of other fintech service providers, including Customers Bancorp, Numerated, and Fountainhead. For some of these manually identified banks, we only have a rough date of automation, potentially creating some noise in our estimation.

Appendix Table A.16 shows summary statistics for the automating banks as well as for the control group of all other small banks.[32] After removing Biz2Credit clients that we do not classify as small banks or that have automation dates after our analysis period, we are left with 20 small banks that automated during the sample period; those banks account for about 75,000 PPP loans in our analysis sample, or 3.8% of all PPP loans originated by small banks. Among automating banks, about half of their total loans occur after automation. Automating banks are somewhat larger than the average small bank.

The Effect of Automation. Appendix Table A.16 shows that, on average, automating banks' share of loans to Black-owned businesses increased after automation, from about 4.1% to about 11.2%. However, this trend could, at least in part, reflect the overall increase in loans to Black-owned businesses over time. To identify a treatment effect of automation, we therefore use a standard differences-in-differences model to evaluate the effect of automation on treated banks relative to other small banks that never automated:

$$\mathbb{1}(\mathrm{BlackOwned}_{i,b,t}) = \alpha_b + \alpha_t + \beta \mathbb{1}(\mathrm{PostAuto}_{b,t}) + \mathbf{X}_i \delta + \varepsilon_{ibt}. \tag{2}$$

We estimate Equation 2 only within the sample of small banks. The dependent variable is an indicator whether PPP loan i made by bank b at time t is to a Black-owned business. Here, $\mathbb{1}(\mathrm{PostAuto}_{b,t})$ is an indicator for bank b having automated—i.e., having started service with Biz2Credit or another white label fintech—as of date t. α_b is a fixed effect for the bank, allowing us to remove the effects of any baseline differences in lending to Black-owned businesses between automating and non-automating banks; α_t is a fixed effect for the week of loan approval, removing the effects of any general time trends in the share of loans by small banks to Black-owned businesses. $\mathbf{X}_i$ represents other loan-level controls. The coefficient of interest β represents the effect of automation.

We report results from estimating Equation 2 in Table 11. In column 1 of Panel A, we report the results of the baseline differences-in-differences model controlling only for bank and time fixed effects. The coefficient implies that the share of loans to Black-owned businesses increased by six percentage points after automation, relative to a pre-automation share of 4.1%. In column 2, we add the same set as of controls as in Table 4, Panel A, column 8. The coefficient remains an economically large and statistically significant 4.3 percentage points: automation more than doubled small banks' propensity to

[31] For non-PPP marketplace loans Biz2Credit uses different user-permissioned data, digital workflows, and AI-based algorithms to make determinations.

[32] It is possible that some of the small banks in the control group also automated at some point before, during, or after the PPP, and we were unable to identify this via our Biz2Credit data and manual search efforts. Any misclassification of banks into the control group will likely bias us against finding an effect.

lend to Black-owned businesses, even conditional on other firm and loan characteristics.[33] In columns 3-5 of Table 11 Panel A, we consider how lending to the other races or ethnicities was affected. We see a small increase in the rate of lending to Hispanic- and Asian-owned firms, suggesting some additional benefit of automation for other minorities. As in our previous analyses of small bank lending, it appears that most of the increase in lending to Black-owned firms came at the expense of White-owned firms.

One possible concern with the empirical design in Equation 2 is that the automating banks may have already been increasing their share of loans to Black-owned businesses prior to the automation event. Indeed, a bank's decision to automate could have been driven by a desire to serve more Black-owned businesses. To assess this concern, we use the following dynamic differences-in-differences specification to examine whether, in the period prior to automation, we see a differential trend in the share of loans extended by automating small banks to Black-owned businesses:

$$\mathbb{1}(\text{BlackOwned}_{ibt}) = \sum_{k \neq -1} \beta_k \mathbb{1}(t - A_b = k) + \alpha_b + \alpha_t + \mathbf{X}_{ibt}\delta + \varepsilon_{ibt}. \tag{3}$$

In Equation 3, A_b is the period in which bank b automates, and $\mathbb{1}(t - A_b = k)$ denotes an indicator for being k periods from that automation date. The coefficients are relative to the omitted period, $k = -1$, which represents the period prior to automation. The model also includes fixed effects for bank and origination period, as well as other controls defined previously.

In Figure 4, we plot the β_k coefficients from the dynamic differences-in-differences model in Equation 3. Panel A shows estimates with only bank and time fixed effects (as in Table 11, Panel A, column 1). Panel B adds the additional vector of controls (as in Table 11, Panel A, column 2). We do not report more than three months before automation because the automation dates (usually in late Spring and late Fall after a period in which the PPP program was in active) mean that we rarely observe PPP loans four months prior to an automation event. The graphs indicate no pre-trend before automation and a clear upwards trend afterwards. In order to eliminate potential compositional effects, we also conduct a robustness check at the weekly level that restricts the sample to a balanced panel of 11 automating banks that have observations at least six weeks on both sides of the automation date. The results, in Appendix Figure A.8, also indicate no pre-trends and a clear discontinuity in the weeks following automation, even though for some of the banks our data do not include the exact week of automation. Overall, the figures demonstrate an immediate and persistent discontinuity around the automation event, consistent with a causal effect of automation on the lending behavior of small banks.

In the last part of this section, we examine whether the effect of automation on the share of loans to Black-owned businesses is larger in areas with higher racial animus. In Panel B of Table 11, we interact our automation dummy with our six indicators for racial animus. We see positive and significant interactions for four of the six measures, with the remaining two positive but insignificant. For example, the interaction coefficient of 0.009 for the implicit bias test implies that, relative to the mean share of

[33] In our baseline analysis, we continue to cluster standard errors by borrower zip code. In Appendix Table A.17, we present the main models with alternative standard errors. We cluster standard errors by bank in columns 1-2, and double cluster standard errors by bank and week approved in columns 4-6. The statistical significance of our results is robust to both approaches.

loans to Black-owned businesses in this small bank sample, automation increased this share by 24% *more* in areas with one standard deviation higher racial animus. The fact that automation has larger effects on the share of loans to Black-owned businesses in areas with higher racial animus provides additional evidence that one of the mechanisms through which automation increases those loans is by reducing the effect of preference-based discrimination.

5 Conclusion

The original legislation authorizing the PPP included an explicit mandate to prioritize socioeconomically disadvantaged businesses. Yet, in practice, many conventional bank lenders did not serve Black-owned businesses in proportion to their share in the PPP borrower population. Instead, it was fintech firms that made a disproportionate share of loans to Black-owned businesses, accounting for over half of the PPP loans to Black-owned businesses. Among conventional lenders, small banks had a particularly low rate of lending to Black-owned businesses. Why would this have occurred given that PPP loans were 100% guaranteed by the federal government? This question is the focus of our paper.

We show that a rich array of basic borrower characteristics—including location, loan amount, loan approval date, industry, and business form—can explain about two-thirds of the disparity between fintechs and other lenders. However, even after these controls, Black-owned businesses remain about 12 percentage points more likely than other firms to get their PPP loan from a fintech lender. Much of this substitution towards fintech lenders comes from a lower propensity of Black-owned businesses to get loans from smaller banks. We show that differential pre-existing bank relationships, real-time revenue, fintech affinity, and firm application behavior cannot fully explain this gap.

We find suggestive evidence consistent with a role for preference-based discrimination à la Becker (1957) in explaining some of the lower rates of lending to Black-owned businesses among smaller conventional lenders. Specifically, we show that the observed differences are larger in areas with higher racial animus. It is important to note that many of the variables we condition on in this analysis—such as bank branch location or the distribution of firms with checking accounts at banks—may be the result of historical patterns of discrimination. It is therefore possible that the substantial differences in our controlled models represent a lower bound for the overall effect of discrimination on lending patterns.

We also present evidence that automation may help explain why disparate treatment is concentrated among smaller banks. We show that after small banks automated their lending processes, their rate of lending to Black-owned businesses increased substantially. This contributes to the ongoing conversation about the equity effects using machine learning algorithms in lending (Fuster et al., 2020; Berg et al., 2020; Blattner et al., 2021; Bartlett et al., 2021). While concerns that algorithms may discriminate because they are trained on biased data are warranted, our results suggest that there may be benefits from automation. Specifically, by eliminating manual review conducted by biased humans, automation could reduce the incidence of taste-based discrimination.

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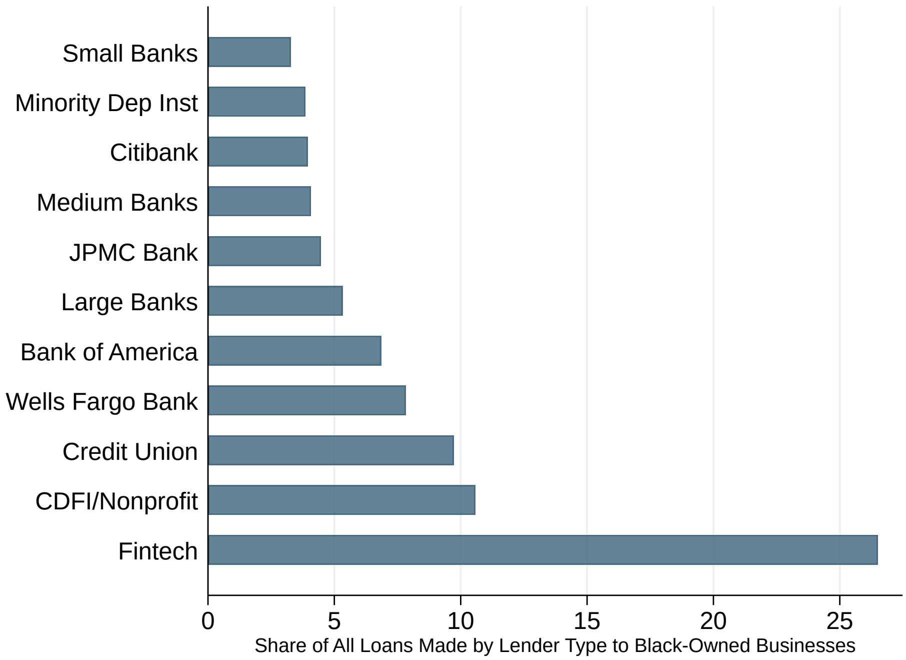
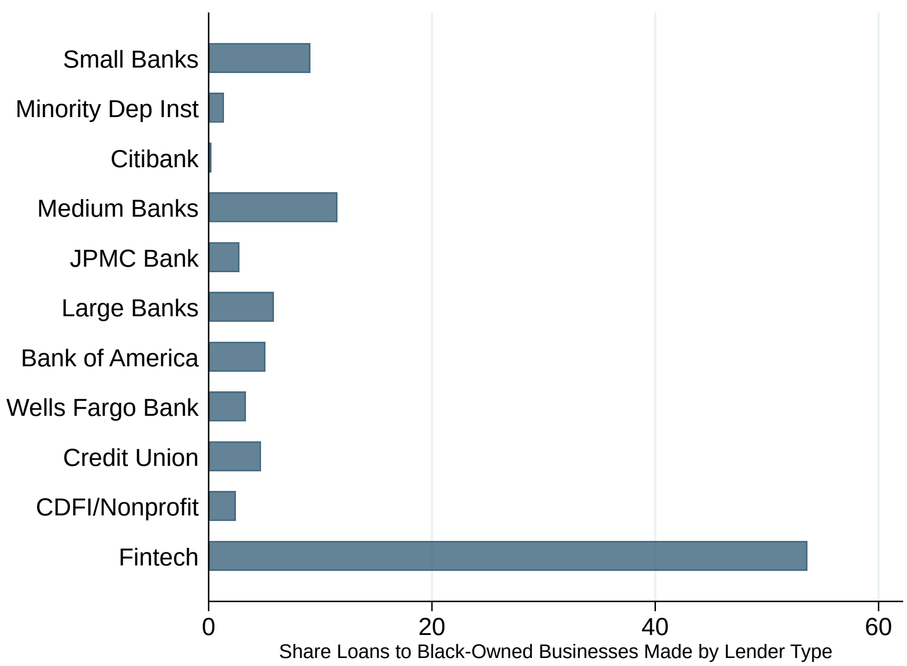
Figure 1: **Black-Owned Business PPP Lending by Institution Type**

(A) Share of PPP Loans to Black-Owned Businesses by Institution Type



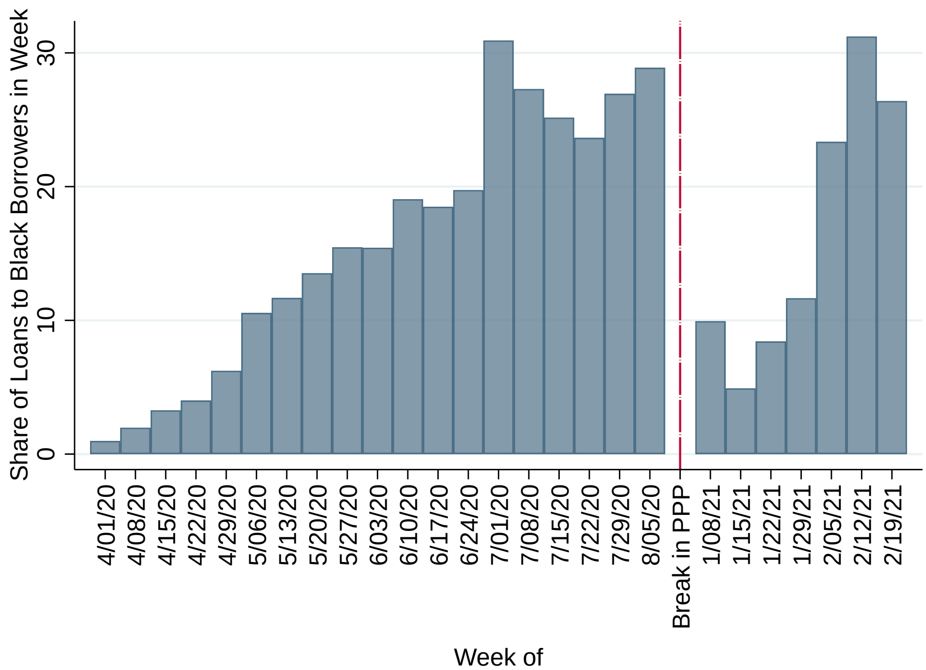
(B) Share of PPP Lender Institution Type among Black-Owned Businesses



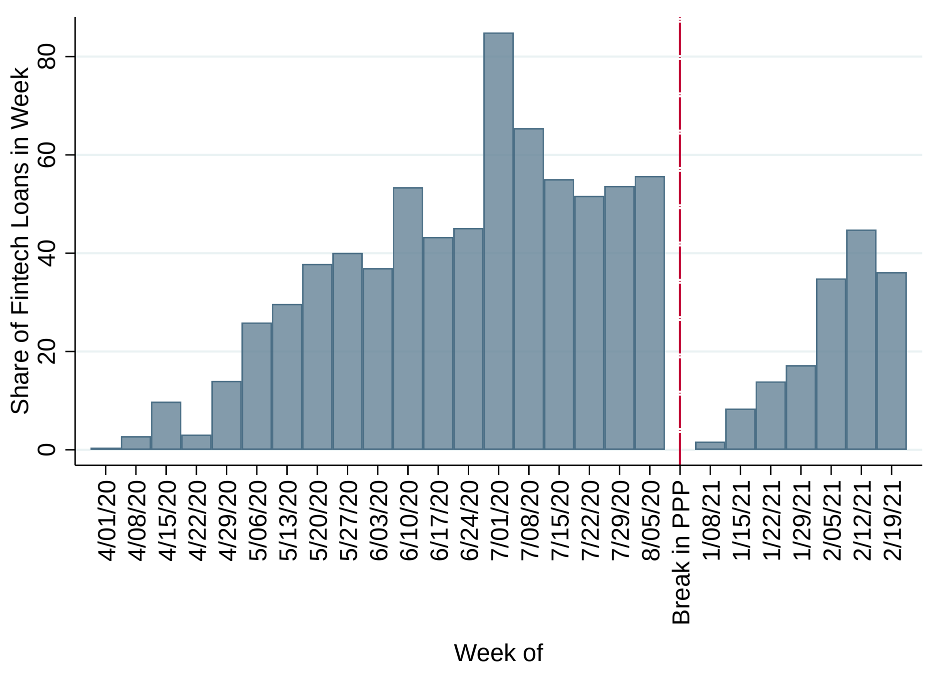
Note: This figure shows the shares of PPP loans made by originating lender type to Black-owned businesses. Panel A shows the Black share of PPP loans made by originating lender type (P(Black-owned|Originating Lender Type)). Panel B shows the shares of PPP loans from originating lender type made to Black-owned businesses (P(Originating Lender Type|Black-owned)).

Figure 2: **Black-Owned Businesses PPP Lending by Week**

(A) Black-Owned Businesses PPP Lending by Week

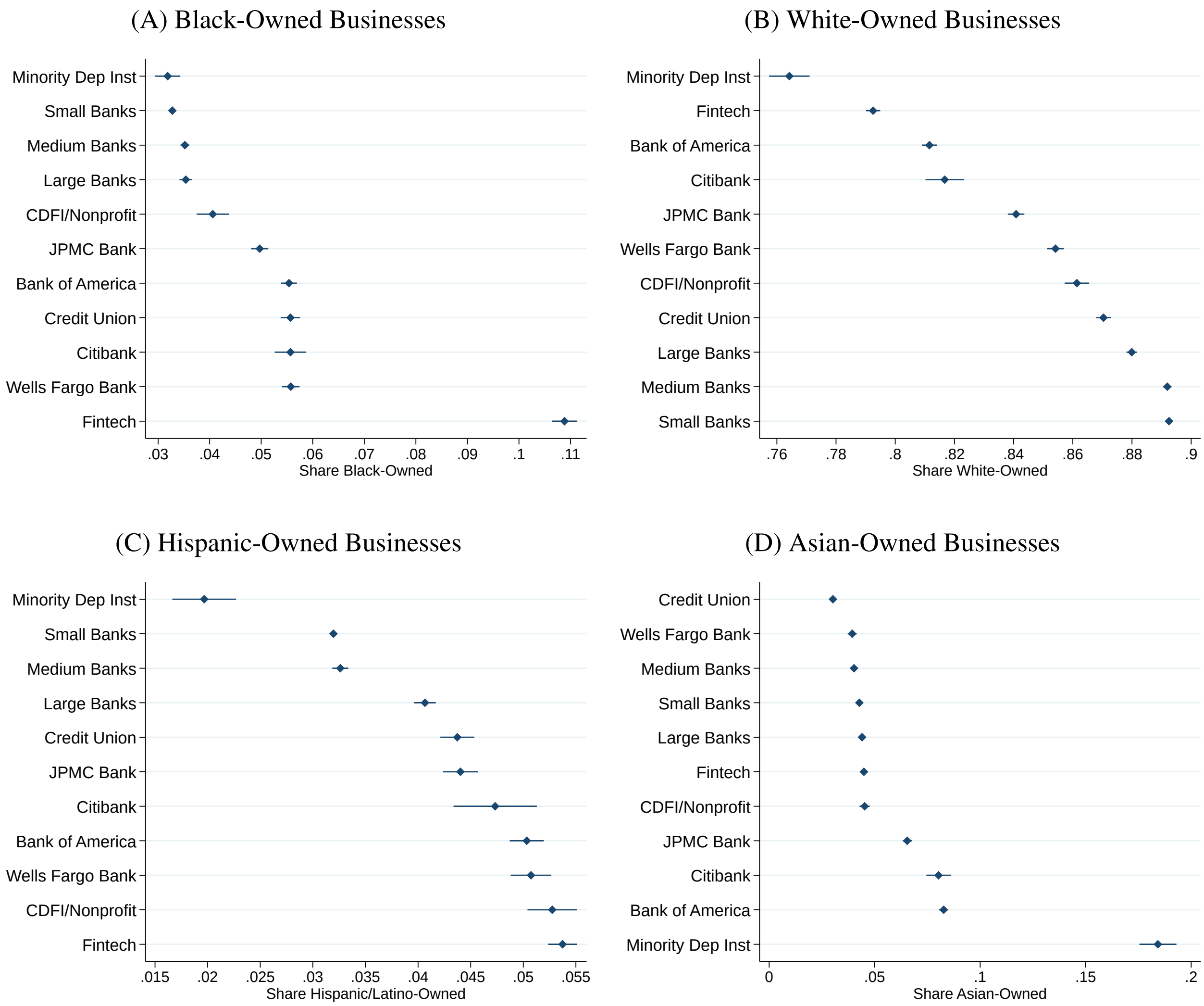


(B) Fintech PPP Lending by Week



Note: This figure shows shares of PPP loans made to Black-owned businesses (Panel A) and made by fintech lenders (Panel B) by week of loan approval. The dashed red line denotes a hiatus in the PPP program from August 2020 to January 2021.

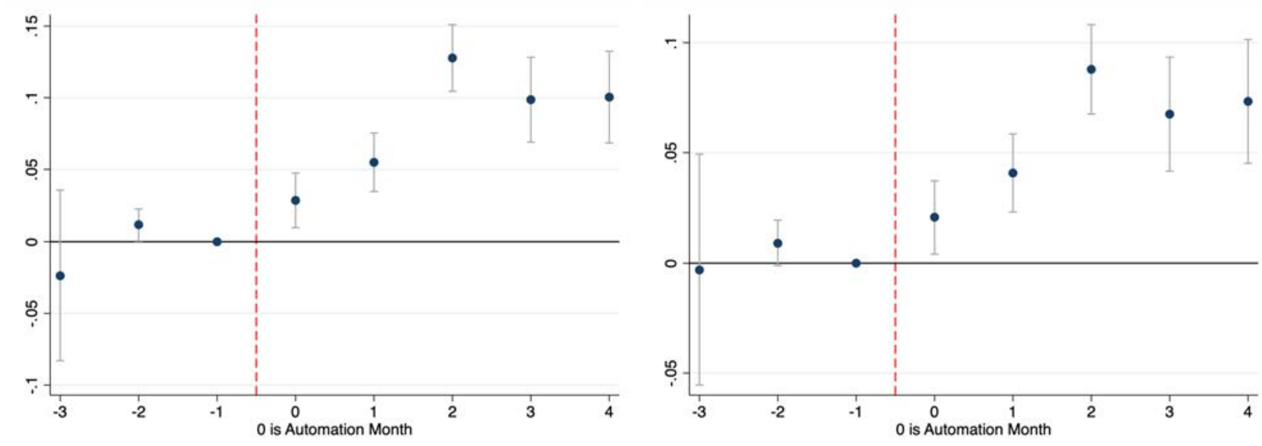
Figure 3: **Conditional Share of PPP Loans to Each Race by Institution Type**



Note: This figure shows shares of PPP loans made to businesses predicted to be Black-owned by originating lender type. Each graph presents coefficients from variants of the following regression: Black-owned$_i = \beta$Lender Type$_i + \gamma \mathbf{X_i} + \epsilon_\mathbf{i}$, where $\mathbf{X_i}$ is a vector of fixed effects for borrower zip code, loan amount percentile (in 100 bins), approval week, 3-digit NAICS industry, business type, and employer status. Standard errors are clustered by zip code. In each panel, we change the dependent variable to be an indicator for whether a borrower is a Black- (Panel A), White- (Panel B), Hispanic- (Panel C), or Asian- (Panel D) owned business.

Figure 4: **Share of Loans to Black-Owned Businesses Before and After Small Bank Automation**

(A) Simple Differences-in-Differences (B) With Additional Controls



Note: This figure reports dynamic differences-in-differences estimates at the monthly level, using Equation 3. Period 0 following the dashed vertical line correspond to the automation month. Panel A includes fixed effects for the bank and week of loan approval. Panel B adds the vector of controls included in Table 11, Panel A, column 1. We do not include more than three months before automation because the automation dates (in late Spring and late Fall after a large gap in the PPP program) mean that we observe essentially no loans made four month prior to . Standard errors are clustered by zip code. The grey bars represent 95% confidence intervals.

Table 1: Summary Statistics by Lender Type

Panel A: All PPP Loans

	Number Lenders	Number Loans	Share Loans	Total Amt ($ bn)	PPP Loan Amount ($) Mean	P10	P50	P90
All	4,889	11,768,450	100%	798.7	67,867	4,199	20,678	124,500
Bank of America	1	491,032	4.2%	34.4	70,080	4,820	20,833	127,855
Citibank	1	47,767	0.4%	4.8	100,359	8,200	29,300	188,900
JPMC Bank	1	438,571	3.7%	41.6	94,745	6,542	27,500	181,897
Wells Fargo Bank	1	280,693	2.4%	13.8	49,179	4,181	18,777	97,042
Large Banks	17	898,175	7.6%	108.8	121,127	6,000	28,133	230,895
Medium Banks	377	2,139,089	18.2%	271.3	126,807	6,080	30,405	266,000
Small Banks	3,196	2,385,728	20.3%	179.0	75,024	4,130	20,832	151,100
Credit Union	946	378,673	3.2%	15.7	41,479	3,602	15,882	82,422
CDFI/Nonprofit	187	1,516,834	12.9%	34.4	22,711	4,400	20,000	20,833
Minority Dep Inst	133	424,976	3.6%	29.3	68,924	3,823	20,053	131,015
Fintech	29	2,766,912	23.5%	65.6	23,726	3,083	17,208	29,166

Panel B: All First Draw PPP Loans Before Feb 24th

	Number Lenders	Number Loans	Share Loans	Total Amt ($ bn)	PPP Loan Amount ($) Mean	P10	P50	P90
All	4,864	5,692,097	100%	533.8	93,784	4,500	20,833	176,100
Bank of America	1	346,477	6.1%	25.6	73,863	4,375	20,833	130,610
Citibank	1	31,341	0.6%	3.4	108,697	8,200	29,800	199,300
JPMC Bank	1	290,131	5.1%	29.7	102,374	6,570	27,597	190,560
Wells Fargo Bank	1	202,027	3.5%	10.5	52,113	4,078	18,520	100,000
Large Banks	17	590,817	10.4%	81.8	138,458	6,200	30,625	258,331
Medium Banks	377	1,405,565	24.7%	197.7	140,632	6,200	33,295	288,874
Small Banks	3,191	1,360,381	23.9%	118.6	87,182	4,524	20,833	173,375
Credit Union	936	227,205	4.0%	10.3	45,402	3,541	15,932	88,900
CDFI/Nonprofit	178	112,320	2.0%	8.2	72,687	3,989	20,800	144,422
Minority Dep Inst	133	201,952	3.5%	18.6	91,885	4,200	20,833	173,500
Fintech	28	923,881	16.2%	29.5	31,921	2,937	15,500	55,782

Panel C: Bank and Credit Relationships Sample (Ocrolus)

	N	SME Has Checking Acct with PPP Lender	Credit With Any: Fintech	Non-Fintech	Monthly Net Cash Inflow ($) Mean	P10	P50	P90
All	216,240	28.5%	14.2%	79.8%	9,124	-36,671	1,374	62,879
Bank of America	15,171	63.9%	15.6%	86.6%	8,755	-45,847	1,433	70,230
Citibank	1,360	53.5%	12.1%	66.2%	10,282	-45,101	1,144	75,981
JPMC Bank	12,616	70.2%	17.5%	89.9%	14,478	-66,644	4,537	111,547
Wells Fargo Bank	8,584	73.7%	13.2%	88.0%	14,451	-34,225	4,069	74,553
Large Banks	21,381	50.0%	14.6%	82.5%	12,188	-42,302	2,584	77,336
Medium Banks	37,338	39.8%	14.5%	75.5%	9,558	-50,997	1,581	76,855
Small Banks	27,580	23.8%	14.2%	75.1%	7,757	-50,065	1,330	71,616
Credit Union	7,255	35.7%	13.0%	71.6%	6,292	-27,811	749	47,421
CDFI/Nonprofit	3,865	8.2%	13.2%	78.0%	7,674	-36,688	1,205	56,613
Minority Dep Inst	4,954	21.6%	13.8%	75.4%	5,410	-52,939	1,117	64,189
Fintech	76,136	0.0%	13.3%	80.3%	7,697	-20,136	946	41,984

Note: This table reports summary statistics about PPP loans by originating lender type, where each PPP lender is assigned to a single type. The data in Panel A include all PPP loans, including "second draw" loans, which is a firm's second PPP loan (accounting for about 2.8 million loans). Panel B repeats the statistics in our starting sample, which is composed of first draw PPP loans between April 3, 2020 and February 23, 2021. All subsequent statistics and analysis are drawn from subsamples of the data included in Panel B. Panel C reports statistics about banking and credit relationships as well as financial performance from those borrowers in the sample of bank statements. The first column, "SME has Checking Account with PPP Lender," means that the borrower's business checking account bank is the same institution that originated their PPP loan. The remaining variables are derived from transactions on the borrowers' most recent monthly bank statement. In this table, we include all loans, regardless of whether race is populated. Appendix Table A.2 repeats Panels B and C for the subset with predicted race.

Table 2: Sample Characteristics

Panel A: Analysis Sample
N = 4,183,623

	Share Loans	Mean Loan Amt ($)	Share Asian Borr	Share Black Borr	Share Hisp Borr	Share White Borr
All	100%	93,666	8.9%	8.6%	7.5%	75.0%
Bank of America	6.4%	75,094	17.9%	6.9%	12.3%	62.9%
Citibank	0.5%	108,719	17.6%	3.9%	10.9%	67.6%
JPMC Bank	5.3%	101,318	14.7%	4.5%	9.6%	71.2%
Wells Fargo Bank	3.7%	52,984	11.9%	7.8%	12.3%	68.0%
Large Banks	9.4%	146,505	7.7%	5.3%	5.5%	81.4%
Medium Banks	24.3%	142,532	6.7%	4.1%	5.3%	84.0%
Small Banks	23.9%	87,164	4.3%	3.3%	3.2%	89.3%
Credit Union	4.1%	45,412	5.2%	9.7%	6.9%	78.1%
CDFI/Nonprofit	2.0%	71,564	7.9%	10.6%	7.1%	74.4%
Minority Dep Inst	3.0%	98,406	25.7%	3.9%	13.6%	56.9%
Fintech	17.4%	31,228	11.2%	26.5%	13.2%	49.2%

Panel B: Bank and Credit Relationships Sample (Ocrolus)
N = 168,360

	Share Loans	Mean Loan Amt ($)	Share Asian Borr	Share Black Borr	Share Hisp Borr	Share White Borr
All	100%	80,897	10.2%	15.3%	11.0%	63.5%
Bank of America	7.1%	67,838	14.9%	9.7%	15.6%	59.7%
Citibank	0.6%	109,947	18.0%	4.3%	14.0%	63.6%
JPMC Bank	5.9%	87,618	13.0%	6.4%	12.7%	67.9%
Wells Fargo Bank	4.0%	53,761	11.4%	9.7%	14.9%	64.0%
Large Banks	9.0%	104,023	9.2%	8.1%	8.1%	74.6%
Medium Banks	16.9%	133,265	7.6%	5.9%	8.3%	78.2%
Small Banks	12.6%	118,637	6.9%	6.1%	6.9%	80.1%
Credit Union	3.4%	56,194	6.7%	14.2%	9.6%	69.5%
CDFI/Nonprofit	1.8%	66,732	8.9%	17.8%	11.9%	61.4%
Minority Dep Inst	2.4%	114,058	34.2%	5.4%	13.3%	47.0%
Fintech	36.3%	42,379	10.0%	28.7%	12.7%	48.6%

Panel C: Application Sample (Lendio)
N = 175,660

	Share Loans	Mean Loan Amt ($)	Share Asian Borr	Share Black Borr	Share Hisp Borr	Share White Borr
All	100%	65,184	10.8%	11.3%	9.5%	68.4%
Conventional	47.7%	88,688	10.1%	6.9%	8.9%	74.0%
Fintech	52.3%	43,765	11.5%	15.3%	10.0%	63.3%

Table 2: Sample Characteristics *(Continued)*

Panel D: Card Revenue Sample (Enigma)
N = 813,812

	Share Loans	Mean Loan Amt ($)	Share Asian Borr	Share Black Borr	Share Hisp Borr	Share White Borr
All	100%	141,529	15.7%	2.8%	6.6%	74.9%
Bank of America	7.5%	93,136	29.3%	4.1%	11.5%	55.1%
Citibank	0.5%	137,962	24.7%	2.5%	11.0%	61.8%
JPMC Bank	5.5%	140,825	21.6%	2.5%	9.4%	66.4%
Wells Fargo Bank	3.8%	68,501	23.2%	4.5%	12.0%	60.3%
Large Banks	11.8%	193,926	11.8%	2.9%	5.3%	79.9%
Medium Banks	29.1%	185,730	10.6%	2.2%	5.2%	82.0%
Small Banks	23.0%	135,672	9.3%	1.7%	3.9%	85.1%
Credit Union	3.4%	80,015	10.8%	3.8%	6.0%	79.4%
CDFI/Nonprofit	2.0%	105,914	13.7%	3.9%	6.6%	75.8%
Minority Dep Inst	3.6%	136,611	42.2%	2.2%	8.9%	46.7%
Fintech	9.7%	57,138	26.0%	5.5%	10.3%	58.2%

Note: This table shows loan characteristics and borrower race and ethnic breakdown by lender type. Panel A includes the analysis sample (all loans for which we can predict race). Panel B restricts to the bank statement-matched sample, which includes borrowers for whom we observe a bank statement *prior* to the PPP loan approval date. Panel C restricts to the Lendio-matched sample. We limit the Lendio sample to borrowers whose loan approval date is after their Lendio application date and are sent to at least one lender by Lendio. Panel D restricts to the Enigma-matched sample. We limit the Enigma sample to borrowers for whom we observe card revenue prior to loan approval.

Table 3: Summary Statistics by Predicted Race

Panel A: Analysis Sample

	All	Asian-Owned	Black-Owned	Hispanic-Owned	White-Owned
Loan Amount					
Mean Loan Amount ($)	93,666	53,492	24,315	54,287	110,317
Median Loan Amount ($)	20,833	20,071	14,886	18,218	$23,700
Share Total Loans Made by Bank Types					
Bank of America	6.4%	12.8%	5.1%	10.5%	5.3%
Citibank	0.5%	1.1%	0.3%	0.8%	0.5%
JPMC Bank	5.3%	8.7%	2.8%	6.8%	5.0%
Wells Fargo Bank	3.7%	4.9%	3.3%	6.0%	3.3%
Large Banks	9.4%	8.1%	5.8%	6.9%	10.2%
Medium Banks	24.3%	18.3%	11.5%	17.1%	27.3%
Small Banks	23.9%	11.4%	9.1%	10.2%	28.4%
Credit Union	4.1%	2.4%	4.7%	3.8%	4.3%
CDFI/Nonprofit	2.0%	1.7%	2.4%	1.9%	2.0%
Minority Dep Inst	3.0%	8.8%	1.4%	5.5%	2.3%
Fintech	17.4%	21.7%	53.6%	30.5%	11.4%
Business Types					
Corporation	27.8%	40.3%	11.2%	28.7%	28.1%
LLC	26.8%	24.4%	19.9%	23.9%	28.1%
Nonprofit	2.8%	1.0%	2.1%	1.5%	3.2%
Other	0.5%	0.4%	0.5%	0.4%	0.5%
Self Employed	8.6%	6.9%	23.6%	13.9%	6.6%
Sole Proprietorship	20.4%	14.9%	38.4%	21.5%	18.8%
Subchapter S Corporation	13.1%	12.0%	4.3%	10.1%	14.6%
Employer Institution	63.4%	73.8%	21.0%	57.8%	67.6%
Industries (3 Digit NAICS)					
Professional/Technical Services	12.7%	7.8%	10.6%	10.8%	13.7%
Ambulatory Health Care Services	7.5%	10.3%	8.2%	6.3%	7.2%
Food and Drinking Services	5.9%	14.7%	3.5%	8.7%	4.8%
Personal and Laundry Services	6.0%	12.0%	15.6%	7.5%	4.0%
Specialty Trade Contractors	5.4%	0.9%	2.2%	6.3%	6.2%
Other	62.6%	54.3%	60.0%	60.4%	64.1%
Observations	4,183,623	372,993	359,366	313,389	3,137,875

Table 3: Summary Statistics by Predicted Race *Continued*

Panel B: Bank and Credit Relationships Sample (Ocrolus)

	All	Asian-Owned	Black-Owned	Hispanic-Owned	White-Owned
Banking Relationships					
Share Checking Acct from Top 4 Banks	47.8%	57.5%	47.1%	61.9%	44.1%
Share Checking Acct from Large Banks	15.8%	13.6%	19.1%	11.6%	16.0%
Share Checking Acct from Small/Medium Banks	27.5%	20.3%	16.5%	19.9%	32.7%
Share Checking Acct from Others	8.9%	8.7%	17.2%	6.7%	7.2%
Credit Relationships					
Share Credit Relationship with Fintech	14.2%	13.2%	7.9%	12.5%	16.2%
Share Credit Relationship with Non-Fintech	80.0%	78.9%	81.4%	85.8%	78.9%
Share Credit with Checking Account Bank	17.6%	18.4%	14.4%	19.5%	17.9%
Cash In/Outflows					
Mean Monthly Cash Inflow ($)	231,390	223,615	81,706	201,382	273,948
Median Monthly Cash Inflow ($)	65,232	70,141	11,636	58,644	87,949
Mean Monthly Cash Outflow ($)	218,738	213,055	72,270	189,775	260,004
Median Monthly Cash Outflow ($)	60,890	67,033	8,960	52,466	82,450
Mean Monthly Net Cash Inflow ($)	9,016	7,426	6,332	8,681	9,977
Median Monthly Net Cash Inflow ($)	1,332	1,232	703	1,698	1,676
Observations	168,360	17,166	25,782	18,531	106,881

Panel C: Application Sample (Lendio)

	All	Asian-Owned	Black-Owned	Hispanic-Owned	White-Owned
Number of Lenders Sent					
All	1.480	1.564	1.464	1.498	1.468
Fintech	0.886	1.024	0.995	0.870	0.852
Conventional	0.594	0.540	0.469	0.628	0.616
Share of Lenders Sent					
Fintech & Conventional	14.7%	16.8%	15.8%	15.4%	14.2%
Fintech Only	55.5%	62.0%	64.4%	53.7%	53.4%
Conventional Only	29.8%	21.2%	19.8%	30.9%	32.4%
Observations	175,660	16,711	17,442	14,644	105,584

Panel D: Card Revenue Sample (Enigma)

	All	Asian-Owned	Black-Owned	Hispanic-Owned	White-Owned
Card Revenue					
Mean (Approval & 2 Prev Mos)	53,968	43,422	23,169	42,557	58,355
Median (Approval & 2 Prev Mos)	24,993	21,320	10,273	21,118	27,178
Observations	813,812	127,957	23,082	53,622	609,151
Struggling (Rev in 2/20, not at Appr)	20.8%	24.0%	24.4%	20.5%	20.0%
Observations	970,270	142,680	30,960	64,077	732,553

Note: This table reports summary statistics by race/ethnicity for our four main samples. Panel A contains loan and firm characteristics for the full analysis sample. Panel B summarizes information from bank statement-matched data. Panel C contains statistics about the data on PPP applications from the Lendio platform, restricted to applications linked to a PPP loan in the SBA data. "Conventional" includes all non-fintech lenders. Panel D summarizes the credit and debit card data. We define firms as "struggling" if they had revenue in February, 2020 but not in the month of approval.

Table 4: Business Owner Race and PPP Lender Type

Panel A: Fintech PPP Loan

Dependent Variable:	$\mathbb{1}$(Fintech)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Black-Owned)	0.397***	0.316***	0.232***	0.269***	0.175***	0.155***	0.148***	0.121***
	(0.005)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Loan Amount FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	No	No	Yes	No	Yes	Yes	No	Yes
Census Tract FE	No	No	No	Yes	No	No	No	No
Approval Week FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	No	Yes
Zip-by-Industry FE	No	No	No	No	No	No	Yes	No
Business Type FE	No	No	No	No	No	No	No	Yes
Employer Status FE	No	No	No	No	No	No	No	Yes
Dep Var Mean	0.174	0.174	0.174	0.174	0.174	0.174	0.174	0.174
R^2	0.086	0.138	0.218	0.188	0.291	0.313	0.390	0.356
Observations	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623

Panel B: Bank PPP Loan

Dependent Variable:	$\mathbb{1}$(Top 4 Bank)		$\mathbb{1}$(Large Bank)		$\mathbb{1}$(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Black-Owned)	-0.049***	-0.008***	-0.039***	-0.025***	-0.301***	-0.081***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Loan Amount FE	No	Yes	No	Yes	No	Yes
Zip Code FE	No	Yes	No	Yes	No	Yes
Approval Week FE	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes
Business Type FE	No	Yes	No	Yes	No	Yes
Employer Status FE	No	Yes	No	Yes	No	Yes
Dep Var Mean	0.159	0.159	0.094	0.094	0.482	0.482
R^2	0.001	0.317	0.001	0.131	0.029	0.376
Observations	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623

Panel C: Other Races

Dependent Variable:	$\mathbb{1}$(Fintech)		$\mathbb{1}$(Top 4 Bank)		$\mathbb{1}$(Large Bank)		$\mathbb{1}$(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Asian-Owned)	-0.319***	-0.121***	0.161***	0.030***	0.023***	0.015***	0.091***	0.032***
	(0.005)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.006)	(0.002)
$\mathbb{1}$(Hispanic-Owned)	-0.231***	-0.083***	0.127***	0.018***	0.011***	0.022***	0.066***	0.037***
	(0.006)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)
$\mathbb{1}$(White-Owned)	-0.422***	-0.129***	0.028***	0.001	0.044***	0.028***	0.350***	0.100***
	(0.005)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Loan Amount FE	No	Yes	No	Yes	No	Yes	No	Yes
Zip Code FE	No	Yes	No	Yes	No	Yes	No	Yes
Approval Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Business Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Employer Status FE	No	Yes	No	Yes	No	Yes	No	Yes
Dep Var Mean	0.174	0.174	0.159	0.159	0.094	0.094	0.482	0.482
R^2	0.108	0.357	0.016	0.317	0.003	0.132	0.068	0.378
Observations	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623

Note: This table reports estimates of Equation 1. The dependent variable in Panel A is an indicator for whether the originating lender is fintech. Panel B repeats the specifications in columns 1 and 8 for indicators for whether the originating lender is a Top-4 bank (columns 1–2), large bank (columns 3–4), and small/medium-sized bank (columns 5–6). Panel C repeats Panel B, but adds two columns for fintech loans and considers the other three races/ethnicities. Here, Black-owned businesses represent the single omitted group, so the coefficients should be interpreted relative to them. Control variables all pertain to the borrower firm and their particular PPP loan. Loan Amount FE are 100 indicator variables for each percentile of the loan size distribution. Zip Code and Census Tract FE are indicators for each zip code and census tract. Approval Week FE are indicators for the week in which the PPP loan was approved by SBA. Industry FE are 104 indicators for NAICS 3-digit classifications that appear in the data. Business type FE are 7 indicators for the firm's business type (see Table 3). Employer status is an indicator for whether the firm has at least one employee. Standard errors are clustered by borrower zip code. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Signal Strength of Black Business Ownership and PPP Lender Type

Panel A: Fintech PPP Loan

Dependent Variable:	𝟙(Fintech)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Black Owned—First Quintile)	0.188***	0.140***	0.087***	0.110***	0.064***	0.056***	0.057***	0.043***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
𝟙(Black Owned—Second Quintile)	0.252***	0.196***	0.149***	0.169***	0.111***	0.100***	0.099***	0.080***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
𝟙(Black Owned—Third Quintile)	0.359***	0.290***	0.233***	0.257***	0.176***	0.158***	0.155***	0.127***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
𝟙(Black Owned—Fourth Quintile)	0.521***	0.429***	0.358***	0.389***	0.275***	0.245***	0.239***	0.193***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
𝟙(Black Owned—Fifth Quintile)	0.663***	0.551***	0.456***	0.500***	0.358***	0.312***	0.299***	0.247***
	(0.006)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Loan Amount FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	No	No	Yes	No	Yes	Yes	No	Yes
Census Tract FE	No	No	No	Yes	No	No	No	No
Approval Week FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	No	Yes
Zip-by-Industry FE	No	No	No	No	No	No	Yes	No
Business Type FE	No	No	No	No	No	No	No	Yes
Employer Status FE	No	No	No	No	No	No	No	Yes
Dep Var Mean	0.174	0.174	0.174	0.174	0.174	0.174	0.174	0.174
R^2	0.104	0.151	0.228	0.199	0.297	0.318	0.393	0.359
Observations	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623

Panel B: Bank PPP Loan

Dependent Variable:	𝟙(Top 4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(First Quantile)	0.018***	-0.002	-0.012***	-0.007***	-0.198***	-0.031***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
𝟙(Second Quantile)	-0.014***	-0.007***	-0.019***	-0.015***	-0.227***	-0.059***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
𝟙(Third Quantile)	-0.038***	-0.009***	-0.035***	-0.026***	-0.286***	-0.086***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
𝟙(Fourth Quantile)	-0.086***	-0.013***	-0.056***	-0.041***	-0.365***	-0.123***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
𝟙(Fifth Quantile)	-0.126***	-0.012***	-0.072***	-0.058***	-0.432***	-0.152***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)	(0.003)
Loan Amount FE	No	Yes	No	Yes	No	Yes
Zip Code FE	No	Yes	No	Yes	No	Yes
Approval Week FE	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes
Business Type FE	No	Yes	No	Yes	No	Yes
Employer Status FE	No	Yes	No	Yes	No	Yes
Dep Var Mean	0.159	0.159	0.094	0.094	0.482	0.482
R^2	0.003	0.317	0.002	0.132	0.031	0.377
Observations	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623

Note: This table reports estimates of Equation 1. The independent variables are quintiles of the probability that the business is Black-owned, within the subset of individuals predicted to be Black by our algorithm. The algorithm predicts an individual to be Black if that is the highest probability race/ethnicity. In the regression models, the omitted group is all borrowers predicted not Black (as in Table 4 Panels A-B). Dependent variables and controls are as described for Table 4. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Black Business Ownership and PPP Lender Type with Bank and Credit Relationship Controls

Panel A: Fintech PPP Loan

Dependent variable:	𝟙(Fintech)			
	(1)	(2)	(3)	(4)
𝟙(Black-Owned)	0.055***	0.055***	0.056***	0.055***
	(0.004)	(0.004)	(0.004)	(0.004)
𝟙(Credit from Fintech)			0.075***	0.078***
			(0.003)	(0.003)
𝟙(Credit from Conv.)			-0.012***	-0.011***
			(0.003)	(0.003)
Loan Amount FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes
Months Since Statement FE	No	Yes	Yes	Yes
Checking Acct Bank FE	No	Yes	Yes	Yes
Monthly Cash Inflow FE	No	No	No	Yes
Monthly Net Cash Inflow FE	No	No	No	Yes
Dep Var Mean	0.363	0.363	0.363	0.363
Observations	168,360	168,360	168,360	168,360

Panel B: Bank PPP Loan

Dependent Variable:	𝟙(Top 4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)		𝟙(PPP Lender is) Checking Acct Bank	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Black-Owned)	0.005	-0.000	-0.017***	-0.019***	-0.047***	-0.036***	-0.017***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)
𝟙(Credit from Fintech)		-0.025***		-0.011***		-0.034***		-0.040***
		(0.003)		(0.002)		(0.003)		(0.004)
𝟙(Credit from Conv.)		0.001		0.005**		-0.002		0.011***
		(0.002)		(0.002)		(0.003)		(0.003)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Months Since Statement FE	No	Yes	No	Yes	No	Yes	No	Yes
Checking Acct Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Monthly Cash Inflow FE	No	Yes	No	Yes	No	Yes	No	Yes
Monthly Net Cash Inflow FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank Statement Sample	Latest	Latest	Latest	Latest	Latest	Latest	Latest	Latest
Dep Var Mean	0.177	0.177	0.090	0.090	0.295	0.295	0.274	0.274
Observations	168,360	168,360	168,360	168,360	168,360	168,360	168,360	168,360

Note: This table reports estimates of Equation 1, focusing on the role of bank and credit relationships. The sample is restricted to bank statement-matched data. We include only information from a firm's latest statement prior to the loan approval. The dependent variable in Panel A is an indicator for whether a PPP loan is originated by a fintech lender. The dependent variables in Panel B are indicators for whether the originating lender is a Top-4 bank (columns 1–2), a large bank (columns 3–4), a small/medium-sized bank (columns 5–6), or the borrower's checking account bank (columns 7–8). We report coefficients on indicators for whether the borrower has previous credit relationships with fintech and non-fintech lenders. Checking Acct Bank FE are indicators for the bank where the borrower has its main business checking account, so that we compare borrowers who bank with the same institution. Monthly Net Cash Inflow FE and Monthly Cash Inflow FE are each a set of 100 percentile indicators for monthly net cash inflow and total cash inflow, respectively. Other controls are as described in Table 4. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Black Business Ownership and PPP Lender Type by Checking Account Bank Type

Dep Var:	Lender is Checking Acct Bank	𝟙(Fintech)	Banks:		
			𝟙(Top 4)	𝟙(Large)	𝟙(Small/Medium)
	(1)	(2)	(3)	(4)	(5)
Panel A: Sample of Borrowers with Checking Accounts at Top 4 Banks					
𝟙(Black-Owned)	-0.006	0.051***	-0.007	-0.010***	-0.034***
	(0.005)	(0.006)	(0.005)	(0.003)	(0.004)
Observations	80,560	80,560	80,560	80,560	80,560
Dep Var Mean	0.248	0.402	0.310	0.048	0.183
Panel B: Sample of Borrowers with Checking Accounts at Non-Top 4 Large Banks					
𝟙(Black-Owned)	-0.024**	0.044***	0.009	-0.033***	-0.036***
	(0.010)	(0.011)	(0.006)	(0.010)	(0.009)
Observations	26,539	26,539	26,539	26,539	26,539
Dep Var Mean	0.261	0.364	0.062	0.309	0.210
Panel C: Sample of Borrowers with Checking Accounts at Small/Medium-Sized Banks					
𝟙(Black-Owned)	-0.015	0.056***	-0.001	-0.008	-0.045***
	(0.010)	(0.010)	(0.005)	(0.005)	(0.010)
Observations	46,352	46,352	46,352	46,352	46,352
Dep Var Mean	0.355	0.256	0.051	0.053	0.577
Panel D: Sample of Borrowers with Fintech Credit Relationship					
𝟙(Black-Owned)	0.019	0.032**	0.016	-0.009	-0.037***
	(0.014)	(0.014)	(0.012)	(0.009)	(0.011)
Observations	23,890	23,890	23,890	23,890	23,890
Dep Var Mean	0.298	0.339	0.194	0.093	0.302
Business Type FE	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes
Checking Acct Bank FE	Yes	Yes	Yes	Yes	Yes
Months Since Statement FE	Yes	Yes	Yes	Yes	Yes
Monthly Cash Inflow FE	Yes	Yes	Yes	Yes	Yes
Monthly Net Cash Inflow FE	Yes	Yes	Yes	Yes	Yes
Credit Rel. Controls	Yes	Yes	Yes	Yes	Yes

Note: This table reports estimates of a modified Equation 1, focusing on various samples of firms with different checking account bank and credit relationships. Panels A, B, and C limit the sample to PPP borrowers with checking accounts at Top-4 banks, non-Top-4 large banks, and small/medium banks, respectively. Panel D limits the sample to PPP borrowers who have previous credit relationship with fintech lenders. Across all panels, the dependent variable in column 1 is an indicator for whether a PPP loan is originated by the borrower's checking account bank. The dependent variables in columns 2–5 are indicators for whether a PPP loan is originated by a fintech lender, Top-4 bank, non-Top-4 large bank, and small/medium bank, respectively. Controls are as described in Tables 4 and 6. Standard errors are clustered by borrower zipcode. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Black Business Ownership and PPP Lender Type with Revenue Controls

Panel A: Controls for Average Revenue in Approval and 2 Previous Months

Dependent variable:	𝟙(Fintech)		Banks: 𝟙(Top 4)		Banks: 𝟙(Large)		Banks: 𝟙(Small/Med)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Black-Owned)	0.016***	0.016***	0.008***	0.008***	-0.002	-0.003	-0.019***	-0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Card Revenue FE	No	Yes	No	Yes	No	Yes	No	Yes
Dep Var Mean	0.097	0.097	0.174	0.174	0.118	0.118	0.521	0.521
Observations	813,812	813,812	813,812	813,812	813,812	813,812	813,812	813,812

Panel B: Sample Restricted to Firms Struggling during Approval Month

Dependent variable:	𝟙(Fintech)	Banks: 𝟙(Top 4)	Banks: 𝟙(Large)	Banks: 𝟙(Small/Med)
	(1)	(2)	(3)	(4)
𝟙(Black-Owned)	0.021***	0.006	-0.011***	-0.019***
	(0.005)	(0.005)	(0.004)	(0.006)
Loan Amount FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes
Dep Var Mean	0.105	0.170	0.119	0.512
R^2	0.205	0.343	0.186	0.367
Observations	203,357	203,357	203,357	203,357

Note: This table reports estimates of a modified Equation 1. In Panel A, we add controls for firm revenue from credit and debit card transactions during and prior to the PPP loan approval month. The sample is restricted to those matched to Enigma data on credit and debit card transactions. We take the mean card revenue over the loan approval month and previous two months, then construct card revenue FE as a set of 100 indicators for each percentile of average monthly card revenue. In Panel B, we restrict the sample to firms that appear especially harmed by the COVID-19 economic crisis. These are firms for which we observe monthly revenue in February 2020 but not in the approval month. Note that we do not observe revenue if there are fewer than 30 transactions. Therefore, these "struggling" firms have either no activity or limited activity relative to February. Other controls are as described in Table 4. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Black Business Ownership and Fintech PPP Loans using Loan Applications via Lendio

Dependent Variable:			𝟙(Fintech PPP)		
	(1)	(2)	(3)	(4)	(5)
𝟙(Black-owned)	0.029***	0.026***	0.028***	0.048***	0.039***
	(0.004)	(0.001)	(0.003)	(0.006)	(0.008)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes
Application Week FE	No	N/A	Yes	Yes	Yes
# Fintech $\times$ # Non-Fintech Sent FE	No	N/A	Yes	Yes	Yes
Lenders Sent	All	N/A	All	Any Conv.	Only Conv.
Sample	Applied via Lendio	Lendio Lenders, Not Applied via Lendio	Applied via Lendio	Applied via Lendio	Applied via Lendio
Dep Var Mean	0.516	0.771	0.516	0.240	0.108
Observations	196,294	692,926	196,294	68,566	45,761

Note: This table reports estimates of a modified Equation 1, focusing on whether Black-owned firms that applied to conventional lenders via the Lendio platform were nonetheless more likely to end up with a fintech PPP loan. The sample is restricted to Lendio applications linked to a PPP loan in the SBA data. The dependent variable is an indicator for whether a PPP loan is originated by a fintech lender. Column 1 includes all merged Lendio applications. Column 2 assesses whether the coefficient magnitude in column 1 relative to Table 4 column 8 reflects Lendio partner lender composition. It uses the sample of non-Lendio PPP loans that were originated by the subset of lenders who appear in the Lendio data. Column 3 repeats column 1 but adds a set of indicators controlling for the number of lenders that an application was sent to in both the fintech and non-fintech ("conventional") categories and indicators for the week of Lendio application. Column 4 restricts the sample to borrowers who were sent to at least one conventional lender. Column 5 restricts the sample to borrowers who were sent only to conventional lenders; that is, borrowers who were sent to both fintech and conventional lenders are excluded from the sample. Other controls are as described in Table 4. Standard errors are clustered by zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Black Business Ownership and Lender Identity: The Effect of Racial Animus

Panel A: Fintech PPP Loans as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	0.121***	0.124***	0.121***	0.120***	0.121***	0.117***	0.107***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
𝟙(Black-Owned) × Animus		0.004**	0.014***	0.013***	0.011***	0.016***	0.029***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Racial Animus Measure		Stephens-Davidowitz	Nationscape	IAT (Implicit)	IAT (Explicit)	Segregation (Dissimilarity)	Segregation (Isolation)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.174	0.174	0.174	0.174	0.174	0.174	0.174
Observations	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623

Panel B: Top-4 Bank PPP Loans as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	-0.008***	-0.009***	-0.008***	-0.009***	-0.008***	-0.008***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
𝟙(Black-Owned) × Animus		0.010***	-0.001	0.008***	0.004***	-0.004***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Racial Animus Measure		Stephens-Davidowitz	Nationscape	IAT (Implicit)	IAT (Explicit)	Segregation (Dissimilarity)	Segregation (Isolation)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.159	0.159	0.159	0.159	0.159	0.159	0.159
Observations	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623

Panel C: Non-Top 4 Bank PPP Loans as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	-0.106***	-0.107***	-0.105***	-0.103***	-0.105***	-0.103***	-0.093***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
𝟙(Black-Owned) × Animus		-0.013***	-0.013***	-0.024***	-0.017***	-0.012***	-0.029***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Racial Animus Measure		Stephens-Davidowitz	Nationscape	IAT (Implicit)	IAT (Explicit)	Segregation (Dissimilarity)	Segregation (Isolation)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.576	0.576	0.576	0.576	0.576	0.576	0.576
Observations	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623

Note: This table reports estimates of a modified Equation 1, focusing on the interaction between the indicator for Black-owned business and a standardized measure of racial animus in the borrower location. The dependent variable differs across the three panels: In Panel A, it is an indicator for a fintech PPP loan, in Panel B, it is an indicator for a Top-4 bank PPP loan, and in Panel C, it is an indicator for a non-Top 4 bank PPP loan. In each panel, column 1 includes the same controls as the specification in Table 4 Panel A column 8. The racial animus measures are as follows: column 2 uses the number of racially charged searches in a designated media market (DMA); column 3 uses responses to the question on favorability toward Black people in the Nationscape survey aggregated to the congressional district level; columns 4–5 use the implicit and explicit score from the Implicit Association Test (IAT) aggregated to the county level; columns 6–7 use the dissimilarity and isolation index at the metropolitan statistical area (MSA) level. All racial animus measures are standardized at their respective levels of geography, weighted by the number of PPP loans. Controls are as described in Tables 4 and 6. Standard errors are clustered by zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Effect of Automation during PPP on Lending to Black-Owned Small Businesses

Panel A: Loan Share by Race and Ethnicity by Bank Automation

Dependent Variable:	$\mathbb{1}$(Black-Owned)		$\mathbb{1}$(Owned by:) Hispanic	Asian	White
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(After Automation)	0.060***	0.043***	0.008***	0.009***	-0.060***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
Bank FE	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	No	Yes	Yes	Yes	Yes
Zip Code FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
Business Type FE	No	Yes	Yes	Yes	Yes
Employer Status FE	No	Yes	Yes	Yes	Yes
Dep Var Mean	0.037	0.037	0.043	0.055	0.865
Observations	2,024,674	2,024,674	2,024,674	2,024,674	2,024,674

Panel B: Loan Share by Race and Ethnicity by Bank Automation and Racial Animus

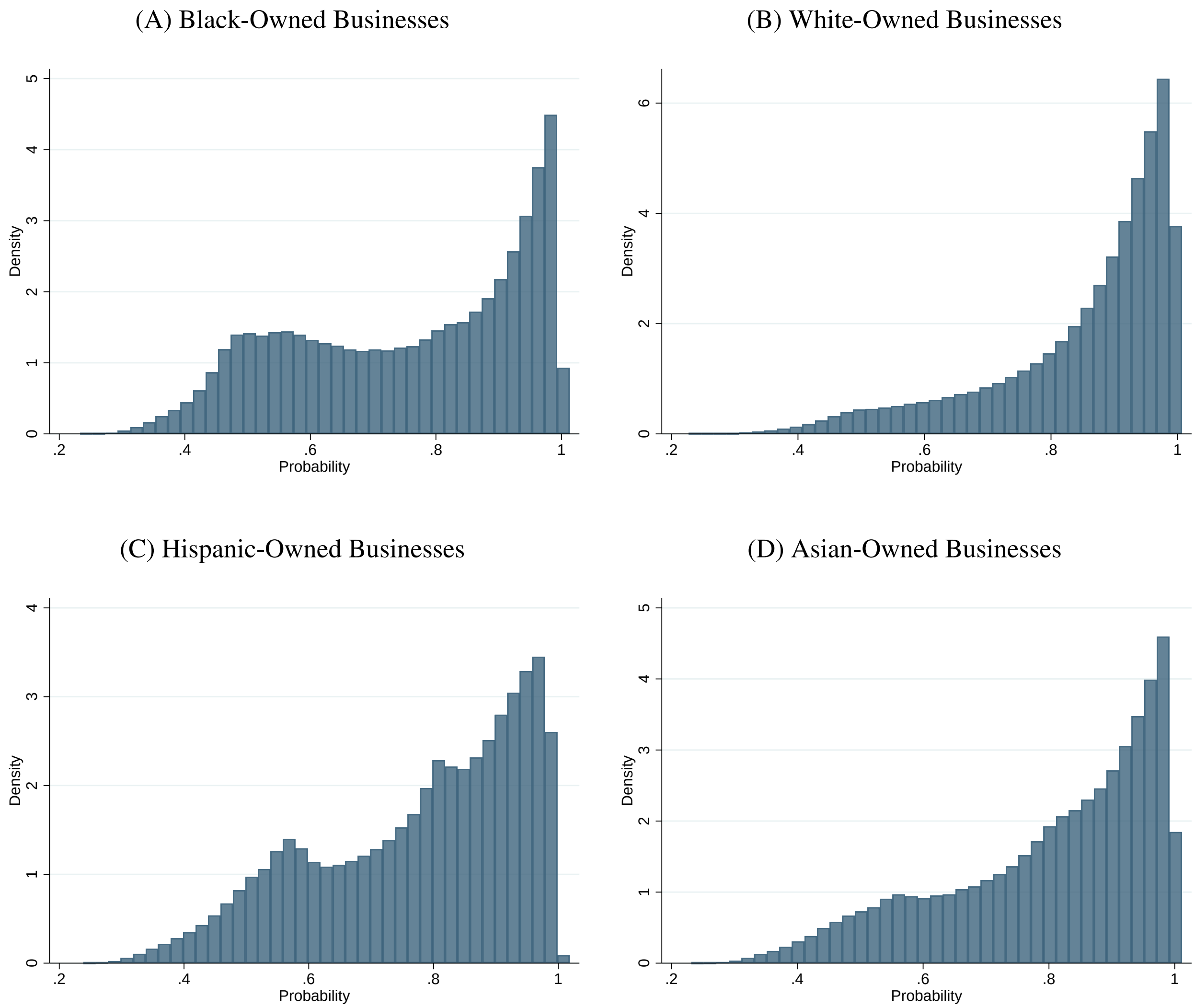
Dependent variable:	$\mathbb{1}$(Black-Owned)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(After Automation)	0.045***	0.042***	0.041***	0.042***	0.037***	0.041***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\mathbb{1}$(After Automation) × Racial Animus	0.004*	0.005	0.009***	0.008***	0.025***	0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Racial Animus Measure	Stephens-Davidowitz	Nationscape	IAT (Implicit)	IAT (Explicit)	Segregation (Isolation)	Segregation (Dissimilarity)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.037	0.037	0.037	0.037	0.037	0.037
Observations	2,024,674	2,024,674	2,024,674	2,024,674	2,024,674	2,024,674

Note: This table reports estimates of Equation 2, estimated on the sample of PPP loans extended by small banks. Columns 1 and 2 of Panel A shows the effect of automation on the probability that a loan is extended to a Black-owned businesses. Columns 3-5 consider effects on lending to Hispanic-, Asian-, and White-Owned businesses, respectively, using the fully controlled model from column 2. Panel B interacts the automation indicator with our measures of local racial animus (from Table 10), continuing to use the fully controlled model from Panel A, column 2. All racial animus measures are standardized at their respective levels of geography, weighted by the number of PPP loans. Controls are as described in Tables 4 and 6. Standard errors are clustered by zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

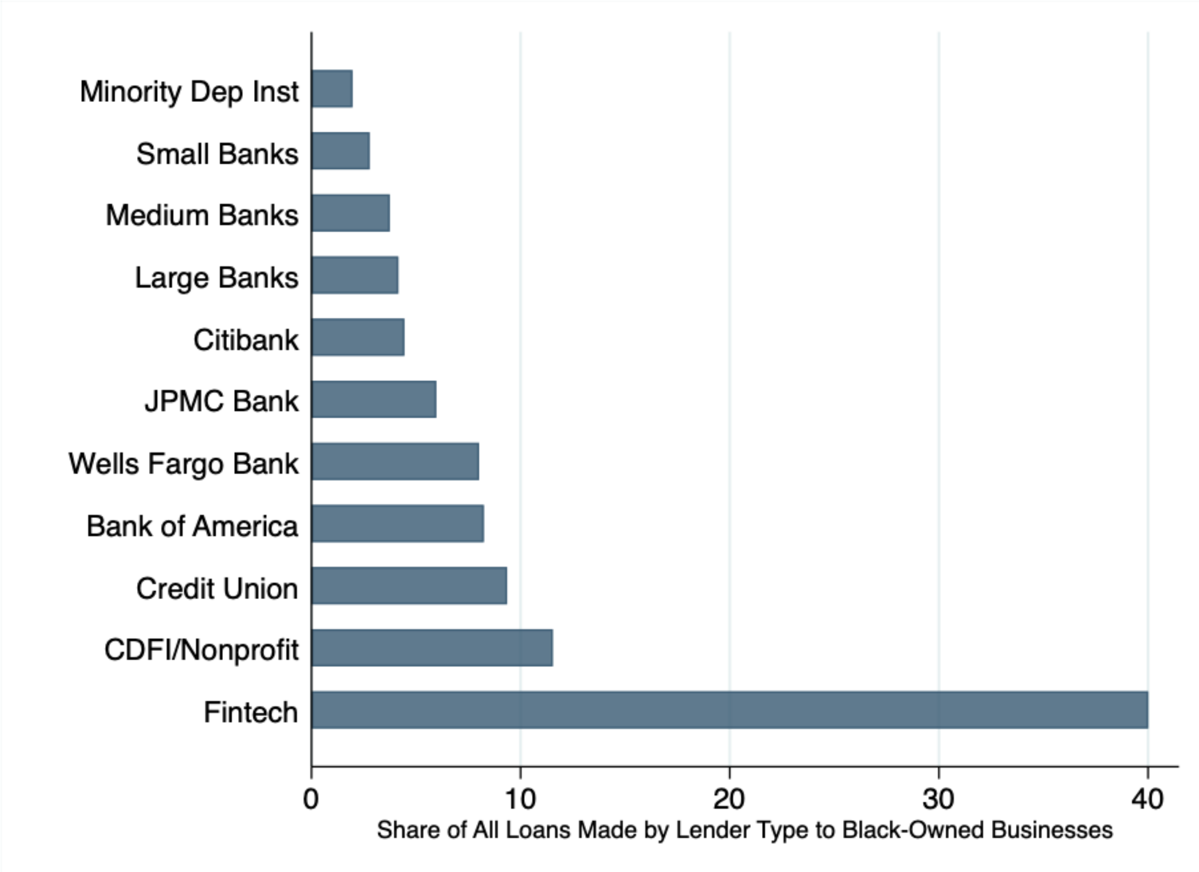
(For Online Publication)

Figure A.1: **Race Probability Distributions**



Note: This figure shows the probability distribution for each race generated by our algorithm. Specifically, each graph contains the sample of borrowers predicted by the algorithm to be the particular race, which means that the race has the highest probability. For example, Panel A contains the subset of borrowers whose highest probability race is Black. The graph shows the algorithm's predicted chance that they are Black.

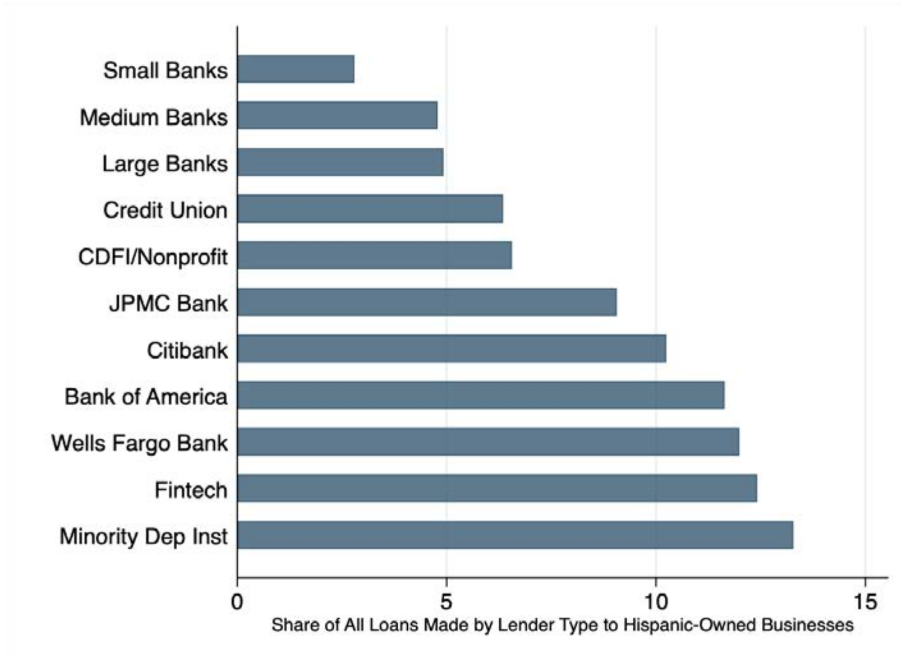
Figure A.2: **Black-Owned Business PPP Lending by Institution Type (Self-Reported)**



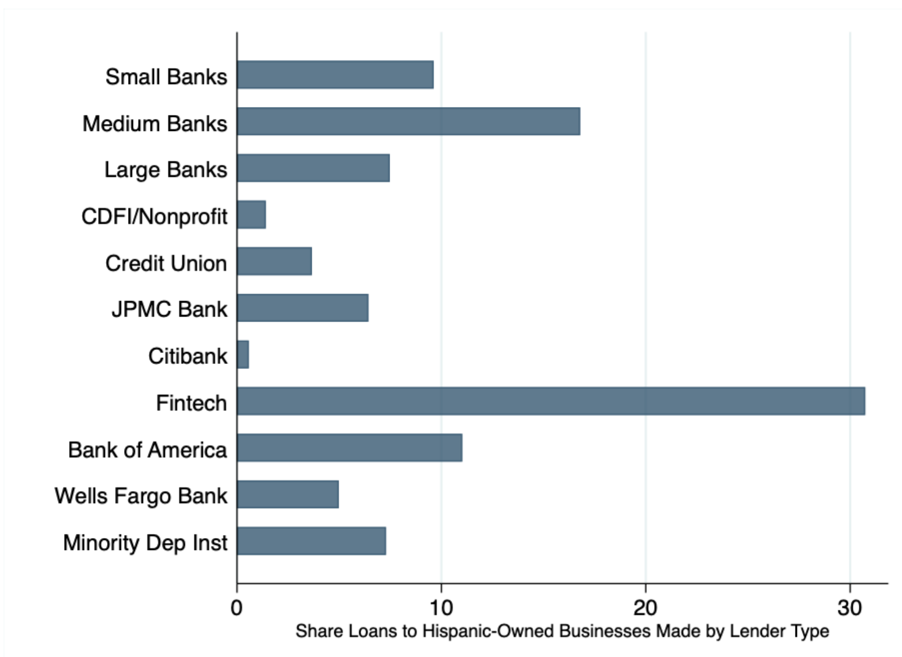
Note: This figure shows shares of PPP loans made to businesses that self-identify as Black-owned by lender type. The sample limits to 1,098,682 loans to businesses for which the data includes self-reported race.

Figure A.3: **Hispanic-Owned Business PPP Lending by Institution Type**

(A) Share of PPP Loans to Hispanic-Owned Business by Institution Type



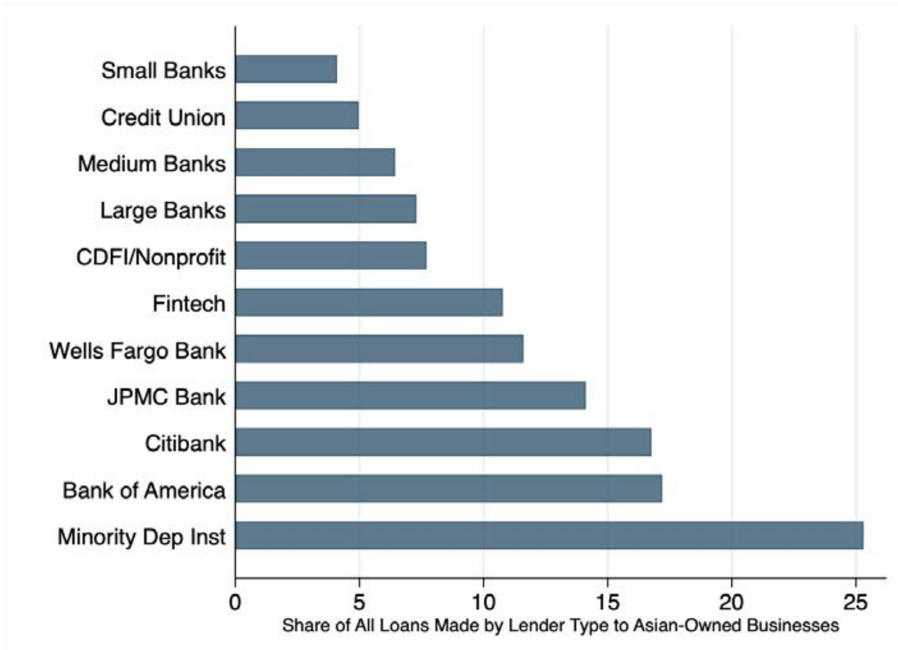
(B) Share of PPP Lender Institution Type among Hispanic-Owned Business



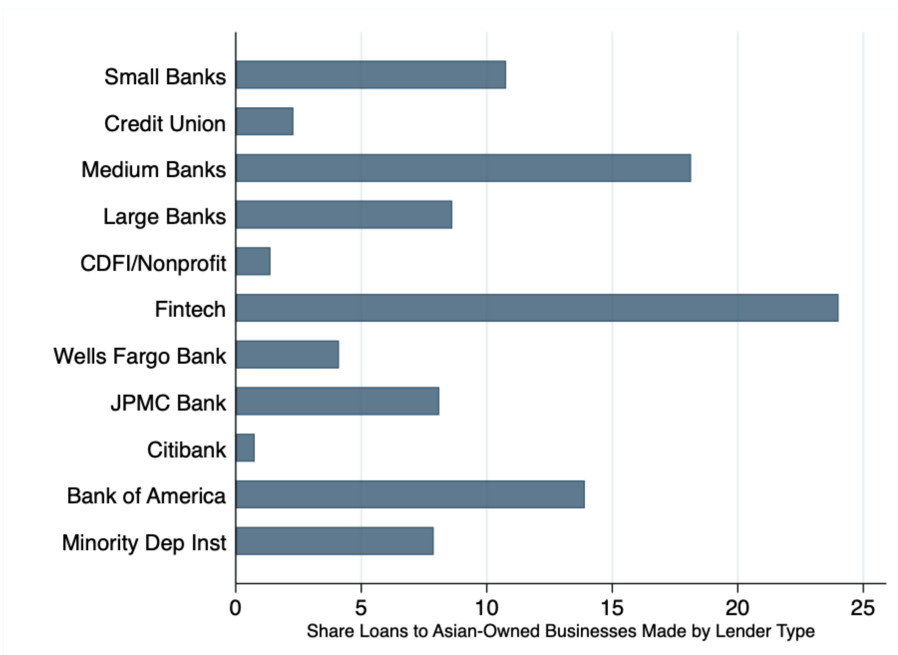
Note: This figure shows the shares of PPP loans made by originating lender type to Hispanic-owned businesses. Panel A shows the Hispanic share of PPP loans made by originating lender type (P(Hispanic-owned|Originating Lender Type)). Panel B shows the shares of PPP loans from originating lender type made to Black-owned businesses (P(Originating Lender Type|Hispanic-owned)).

Figure A.4: **Asian-Owned Business PPP Lending by Institution Type**

(A) Share of PPP Loans to Asian-Owned Business by Institution Type



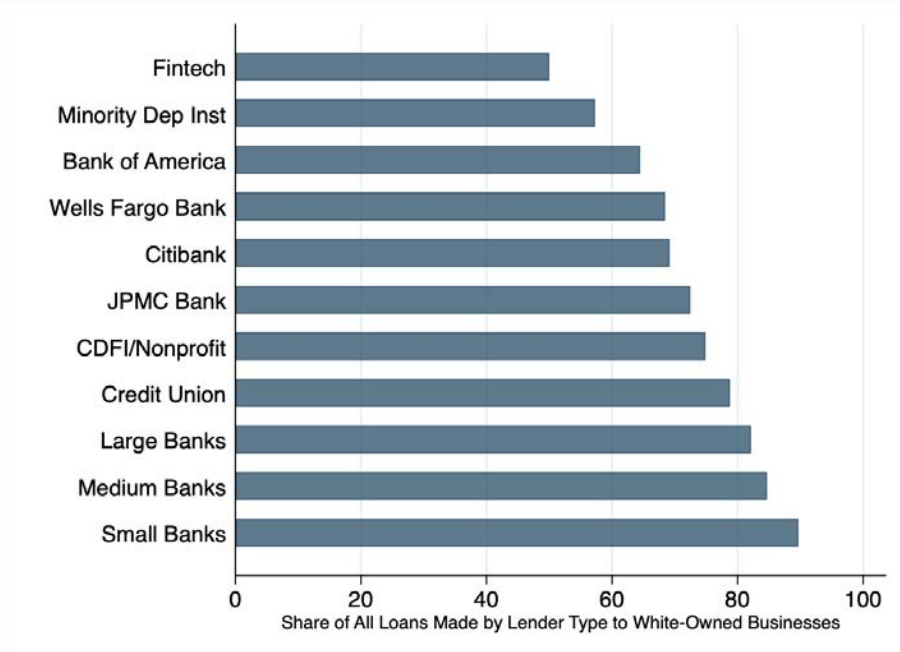
(B) Share of PPP Lender Institution Type among Asian-Owned Business



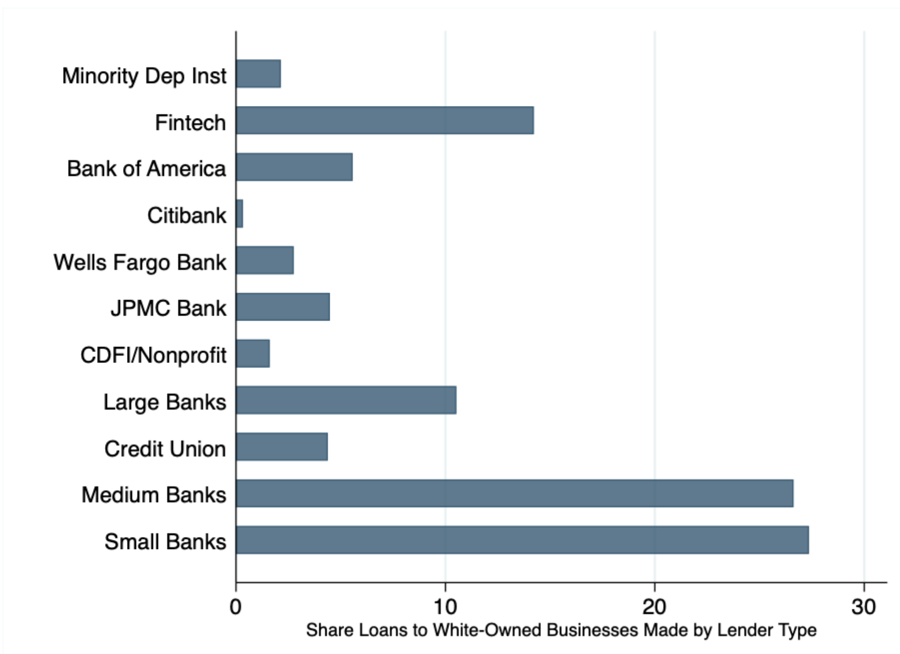
Note: This figure shows the shares of PPP loans made by originating lender type to Asian-owned businesses. Panel A shows the Asian share of PPP loans made by originating lender type (P(Asian-owned|Originating Lender Type)). Panel B shows the shares of PPP loans from originating lender type made to Asian-owned businesses (P(Originating Lender Type|Asian-owned)).

Figure A.5: **White-Owned Business PPP Lending by Institution Type**

(A) Share of PPP Loans to White-Owned Business by Institution Type



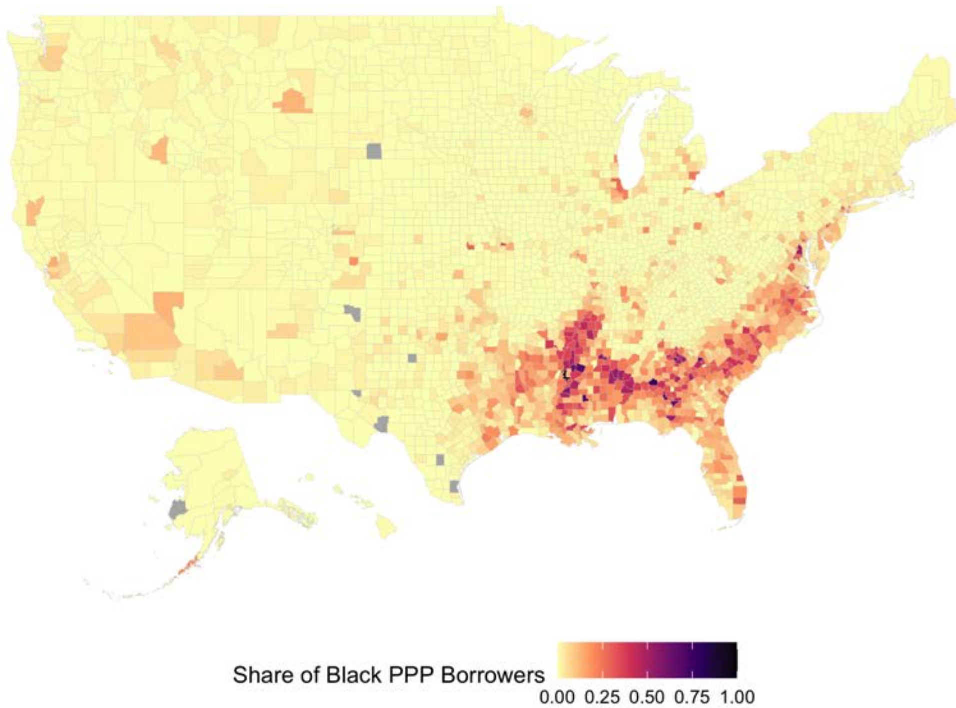
(B) Share of PPP Lender Institution Type among White-Owned Business



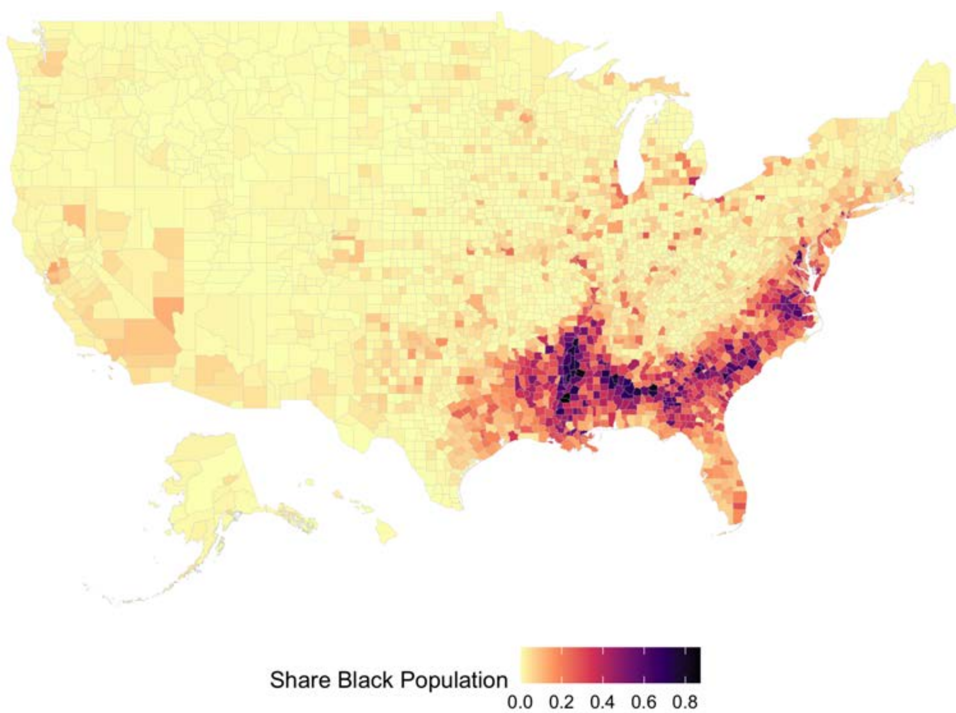
Note: This figure shows the shares of PPP loans made by originating lender type to White-owned businesses. Panel A shows the White share of PPP loans made by originating lender type (P(White-owned|Originating Lender Type)). Panel B shows the shares of PPP loans from originating lender type made to White-owned businesses (P(Originating Lender Type|White-owned)).

Figure A.6: **Geographic Distribution of PPP Loans to Black-Owned Businesses**

(A) PPP Borrowers (Analysis Sample)



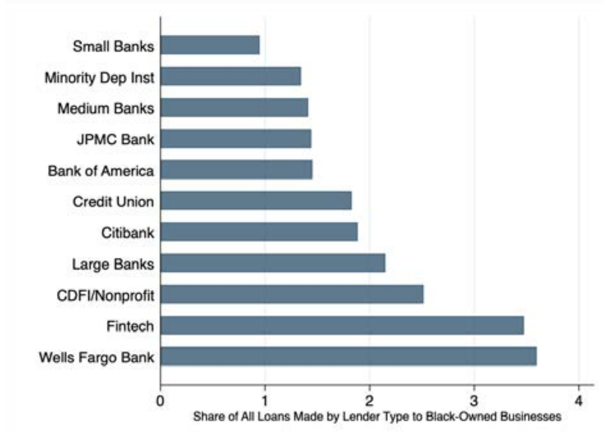
(B) Black Share of Population



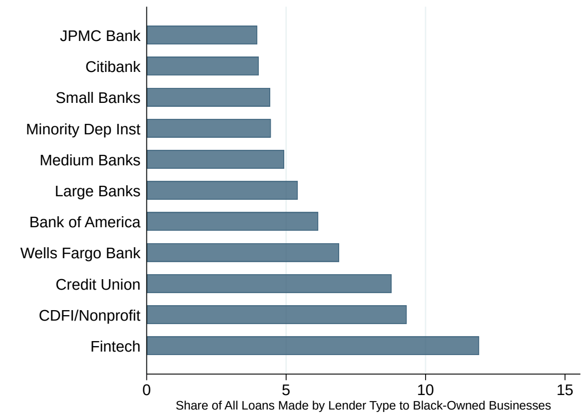
Note: Panel A of this figure shows the geographic distribution of PPP loans to Black-Owned businesses. Panel B shows the geographic distribution of the Black population, measured as the share of Black people in the county. These data are from the 2019 U.S. Census Bureau ACS.

Figure A.7: **Black-Owned Business PPP Lending by Institution Type and Round**

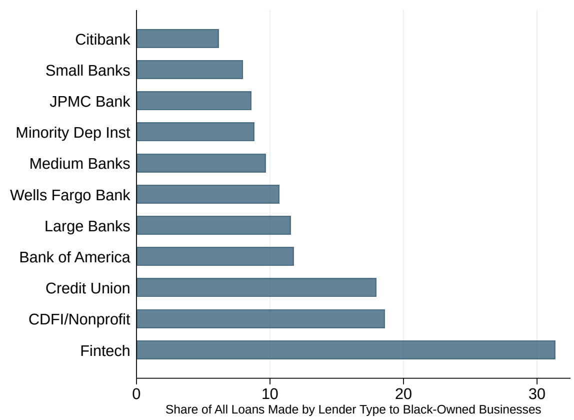
(A) Round 1 (4/3/2020–4/16/2020)



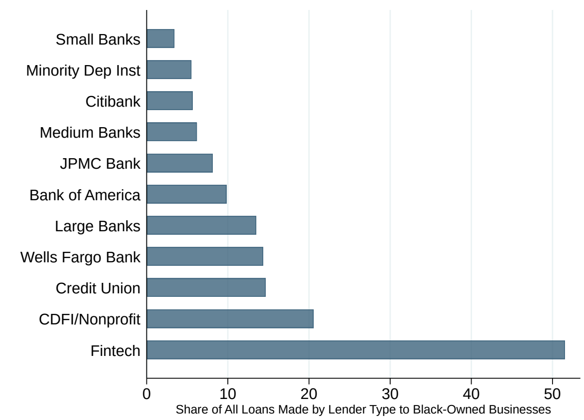
(B) Round 2 Early (4/27/2020–5/13/2020)



(C) Round 2 Late (5/14/2020–8/9/2020)

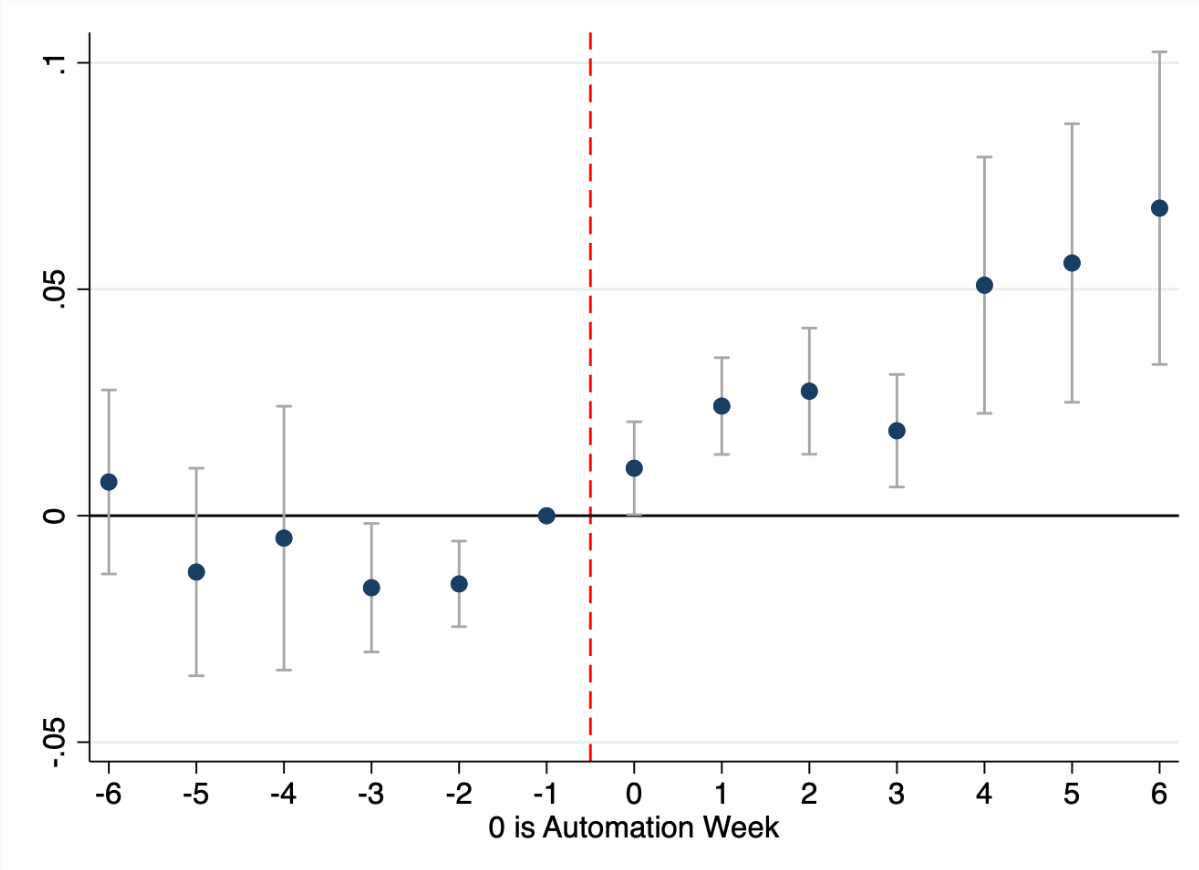


(D) Round 3 (1/12/2021–2/23/2021)



Note: This figure shows the shares of PPP loans made by originating lender type to Black-owned businesses by PPP round. Panel A limits the sample to Round 1 PPP approvals. Panel B limits the sample to Round 2 early approvals. Panel C limits the sample to Round 2 late approvals. We distinguish Round 2 late from early (where early is intended to represent the initial rush) by defining early as ending on the last day on which there were at least 30,000 loans issued. The results are not sensitive to using an alternative threshold. Panel D limits the sample to Round 3 approvals.

Figure A.8: **Weekly Balanced Sample Event Study for the Share of Loans to Black-Owned Businesses Before and After Small Bank Automation**



Note: This figure reports dynamic differences-in-differences estimates, using Equation 3. We employ a weekly balanced panel. Here, we only include the 11 automating banks that have observations at least six weeks on both sides of the automation date. We include bank and time fixed effects (as in Table 11 Panel A column 1). Standard errors are clustered by zip code. The grey bars represent 95% confidence intervals.

Table A.1: List of fintechs

Lender	Num Loans	Median Loan Amt (Thou)	Share Black Borrowers
Cross River Bank	174,436	18,540	0.250
Kabbage	137,687	10,416	0.275
Celtic Bank Corporation	125,601	9,569	0.183
Lendio	101,828	25,000	0.074
WebBank	64,522	13,750	0.098
Customers Bank	61,993	11,524	0.112
Readycap Lending	40,272	20,800	0.056
Itria Ventures	24,459	17,102	0.430
Intuit Financing	14,472	18,424	0.044
Newtek Small Business Finance	13,018	16,500	0.111
Fundbox	11,401	12,588	0.234
MBE Capital Partners	5,330	15,980	0.413
FC Marketplace	5,072	25,486	0.077
Harvest Small Business Finance	4,298	76,298	0.045
Fountainhead SBF	2,684	70,000	0.061
CRF Small Business Loan Company	2,137	20,800	0.175
Sunrise Banks National Association	1,749	23,900	0.094
Accion	1,298	13,211	0.054
Fund-Ex Solutions Group	1,172	75,000	0.044
The Bancorp Bank	1,159	68,700	0.020
Centerstone SBA Lending	980	63,850	0.012
Grow America Fund	593	29,517	0.202
Evolve Bank and Trust	517	25,000	0.128
NBKC Bank	303	14,600	0.079
immito	159	23,000	0.302
Loan Source	150	25,000	0.060
BayBank	145	21,526	0.014
VelocitySBA	81	77,200	0.012
All	797,516	15,777	0.184

Note: This table lists the firms we identify as fintech lenders. We report their number of loans, their median loan amount, and the share of their PPP loans made to Black-owned businesses.

Table A.2: Summary Statistics by Lender Type for Sample with Predicted Race

Panel A: All First Draw PPP Loans Before Feb 24th with Race Prediction

	Number Lenders	Number Loans	Share Loans	Total Amt ($ bn)	PPP Loan Amount ($)			
					Mean	P10	P50	P90
All	4,846	4,212,001	100%	394.4	93,642	4,465	20,833	176,900
Bank of America	1	267,283	6.3%	20.1	75,217	4,500	20,833	134,225
Citibank	1	22,973	0.5%	2.5	108,931	8,200	29,500	200,000
JPMC Bank	1	221,750	5.3%	22.5	101,379	6,465	27,442	188,998
Wells Fargo Bank	1	153,416	3.6%	8.1	53,110	4,160	18,825	102,794
Large Banks	17	411,150	9.8%	59.0	143,532	6,200	31,500	272,847
Medium Banks	377	1,022,007	24.3%	145.8	142,626	6,200	33,600	295,600
Small Banks	3,186	1,000,417	23.8%	87.2	87,183	4,509	20,833	174,500
Credit Union	926	173,966	4.1%	7.9	45,462	3,550	16,000	89,600
CDFI/Nonprofit	176	82,547	2.0%	5.9	71,615	3,906	20,800	145,833
Minority Dep Inst	132	127,778	3.0%	12.6	98,436	4,800	22,100	190,217
Fintech	28	728,714	17.3%	22.8	31,274	2,855	15,343	54,564

Panel B: Bank and Credit Relationships Sample with Race Prediction (Ocrolus)

	N	SME Has Checking Acct with PPP Lender	Credit With Any:		Monthly Net Cash Inflow ($)			
			Fintech	Non-Fintech	Mean	P10	P50	P90
All	169,818	27.7%	14.2%	80.1%	9,047	-36,399	1,340	62,189
Bank of America	12,036	64.1%	15.7%	86.9%	8,278	-47,275	1,479	69,427
Citibank	1,084	51.8%	12.0%	66.1%	9,706	-45,705	961	78,408
JPMC Bank	9,917	69.7%	17.7%	90.0%	15,144	-64,159	4,641	112,415
Wells Fargo Bank	6,805	73.5%	13.0%	87.8%	14,252	-35,662	3,949	78,582
Large Banks	16,032	49.4%	14.6%	82.5%	12,186	-42,680	2,551	77,493
Medium Banks	28,595	38.7%	14.5%	75.5%	9,445	-51,446	1,494	76,657
Small Banks	21,362	22.7%	14.4%	75.4%	7,655	-51,202	1,254	71,749
Credit Union	5,670	34.6%	13.1%	72.1%	6,821	-27,779	829	49,106
CDFI/Nonprofit	3,060	8.5%	13.7%	79.2%	8,311	-36,405	1,189	57,953
Minority Dep Inst	4,003	21.4%	14.2%	75.5%	5,395	-54,560	1,169	63,714
Fintech	61,254	0.0%	13.3%	80.7%	7,580	-19,331	932	40,861

Note: This table reports summary statistics about PPP loans by originating lender type, where each PPP loan is assigned to a single type. We restrict the sample to loans for which we can predict the business owner's race. In Panel B, the first column, "SME has Checking Account with PPP Lender" means that the borrower's business checking account bank is the same institution that originated their PPP loan. The remaining variables are derived from transactions on the borrowers' most recent monthly bank statement.

Table A.3: Race Prediction Out of Sample Confusion Matrix

Panel A: Prediction in Full Self-Identified Sample

	Predicted					
Observed	Asian	Black	Hispanic	Other	White	All
Asian	10.7%	0.0%	0.0%	N/A	0.4%	11.2%
Black	0.0%	9.1%	0.0%	N/A	0.33%	9.5%
Hispanic	0.0%	0.0%	9.7%	N/A	0.6%	10.3%
Other	N/A	N/A	N/A	N/A	N/A	2.7%
White	0.1%	0.1%	0.1%	N/A	69.6%	69.8%
All	10.8%	9.6%	9.8%	N/A	69.9%	100%

Panel B: Prediction in Hold-Out Self-Identified Sample

	Predicted					
Observed	Asian	Black	Hispanic	Other	White	All
Asian	7.8%	0.2%	0.2%	0.0%	2.2%	10.4%
Black	0.1%	5.7%	0.2%	0.0%	3%	9.0%
Hispanic	0.2%	0.3%	5.9%	0.0%	2.8%	9.2%
Other	0.2%	0.2%	0.1%	0.0%	1.8%	2.3%
White	1.5%	1.2%	1.5%	0.0%	64.9%	69.1%
All	9.8%	7.6%	7.9%	0.0%	74.7%	100%

Panel C: Summary Statistics of Race Probability Distributions

	N	Mean	Median	SD
Predicted Asian-Owned	372,993	0.801	0.846	0.166
Predicted Black-Owned	359,366	0.758	0.796	0.186
Predicted Hispanic-Owned	313,389	0.776	0.814	0.167
Predicted White-Owned	3,137,875	0.851	0.902	0.143

Note: Panel A of this table shows the race prediction of the random forest model for the full sample of self-reported individuals with geolocated addresses, including those on which the model was trained. We do not retain the Other prediction or use it in analysis. The sample is 809,119. Panel B of this table shows the out-of-sample validation of the random forest model. It is restricted to the hold-out sample of self-reported borrowers that was not used to train the random forest model, and contains 234,632 observations. (The random forest model with 1,000 trees was trained on 574,487 observations with self-reported race.) In both Panel A and B, the percents represent percent of total observations in the sample. Panel C contains summary statistics about the probability distributions by predicted race/ethnicity.

Table A.4: Additional Sample Characteristics

	Full PPP Sample N = 5,663,719		PPP Analysis Sample N = 4,183,623		Matched to Ocrolus N = 168,360	
	Mean	P50	Mean	P50	Mean	P50
Lender Type						
Bank of America	6.1%		6.4%		7.1%	
Citibank	0.6%		0.5%		0.6%	
JPMC Bank	5.1%		5.3%		5.9%	
Wells Fargo Bank	3.6%		3.7%		4.0%	
Large Banks	10.1%		9.4%		9.0%	
Medium Banks	24.8%		24.3%		16.9%	
Small Banks	24.0%		23.9%		12.6%	
Credit Union	4.0%		4.1%		3.4%	
CDFI/Nonprofit	2.0%		2.0%		1.8%	
Minority Dep Inst	3.6%		3.0%		2.4%	
Fintech	16.3%		17.4%		36.3%	
Borrower Firm Business Type						
Corporation	27.0%		27.8%		31.6%	
LLC	28.9%		26.8%		31.6%	
Nonprofit	3.4%		2.8%		1.0%	
Other	0.6%		0.5%		0.3%	
SelfEmployed	7.8%		8.6%		8.5%	
Sole Proprietorship	19.5%		20.4%		16.9%	
Subchapter S Corporation	12.8%		13.1%		10.2%	
Borrower Firm Characteristics						
Employer Status	64.6%		63.4%		68.1%	
Loan Amount ($)	93,802	20,833	93,666	20,833	80,897	21,121
Borrower Firm Industry						
Professional/Technical Services	12.5%		12.7%		13.7%	
Ambulatory Health Care Services	7.5%		7.5%		6.5%	
Food and Drinking Services	5.9%		5.9%		6.5%	
Personal and Laundry Services	5.8%		6.0%		6.2%	
Specialty Trade Contractors	5.4%		5.4%		5.5%	
Other	62.8%		62.6%		61.6%	
Borrower Firm Census Divisions						
East North Central	13.3%		14.8%		12.3%	
East South Central	5.2%		5.2%		3.0%	
Middle Atlantic	12.6%		8.9%		10.4%	
Mountain	7.2%		7.3%		7.1%	
New England	4.9%		5.4%		3.8%	
Pacific	15.3%		16.7%		22.8%	
South Atlantic	19.4%		20.6%		26.6%	
West North Central	9.6%		9.3%		2.8%	
West South Central	11.7%		11.7%		11.2%	
Borrower Race/Ethnicity						
Share Black-Owned			8.6%		15.3%	
Share Hispanic/Latino-Owned			7.5%		11.0%	
Share Asian-Owned			8.9%		10.2%	
Share White-Owned			75.0%		63.5%	

Note: This table shows additional summary statistics across three samples: the sample with all PPP loans, analysis sample for which we have successfully predicted borrower race, and the bank statement-matched sample. We highlight the distribution of the top-five 3-digit NAICS industries, and code the rest as "Other."

Table A.5: Sample Characteristics for Employers and Non-employer Firms

Panel A: Analysis Sample - Employers
N = 2,695,027

	Share Loans	Mean Loan Amt ($)	Share Asian Borr	Share Black Borr	Share Hisp Borr	Share White Borr
All	100%	140,318	10.4%	2.9%	6.9%	79.8%
Bank of America	7.6%	95,213	19.6%	4.2%	12.7%	63.5%
Citibank	0.6%	151,187	19.4%	2.5%	10.8%	67.3%
JPMC Bank	6.3%	129,937	15.7%	2.4%	9.8%	72.1%
Wells Fargo Bank	3.9%	73,101	13.9%	3.7%	13.0%	69.4%
Large Banks	11.4%	185,867	8.0%	2.9%	5.3%	83.7%
Medium Banks	28.5%	186,355	7.1%	1.8%	5.2%	85.9%
Small Banks	22.9%	134,582	5.7%	1.4%	3.5%	89.4%
Credit Union	3.6%	73,705	6.3%	3.9%	6.6%	83.2%
CDFI/Nonprofit	1.9%	109,627	8.7%	4.3%	6.1%	80.9%
Minority Dep Inst	3.2%	139,354	32.2%	1.9%	11.0%	54.9%
Fintech	10.0%	66,944	15.6%	8.2%	11.4%	64.8%

Panel B: Analysis Sample - Non-Employers
N = 1,547,701

	Share Loans	Mean Loan Amt ($)	Share Asian Borr	Share Black Borr	Share Hisp Borr	Share White Borr
All	100%	11,825	6.4%	18.7%	8.7%	66.2%
Bank of America	4.3%	11,625	12.3%	15.3%	11.5%	60.9%
Citibank	0.5%	16,377	13.7%	7.1%	11.2%	68.0%
JPMC Bank	3.6%	12,322	11.6%	10.9%	9.4%	68.1%
Wells Fargo Bank	3.2%	11,220	7.8%	16.5%	11.0%	64.8%
Large Banks	5.9%	12,127	6.7%	13.5%	6.4%	73.4%
Medium Banks	16.7%	12,247	5.4%	10.9%	5.5%	78.1%
Small Banks	25.0%	12,006	2.0%	6.4%	2.7%	88.8%
Credit Union	5.0%	10,095	3.9%	17.2%	7.4%	71.5%
CDFI/Nonprofit	2.1%	10,832	6.6%	20.7%	9.0%	63.7%
Minority Dep Inst	2.7%	11,372	12.0%	8.2%	19.0%	60.9%
Fintech	31.0%	11,741	8.7%	36.6%	14.2%	40.5%

Note: This table shows loan characteristics and borrower race and ethnic breakdown by lender type for employer firms (Panel A) and non-employer firms (Panel B).

Table A.6: Fintech PPP Loans and the Zip Code's Black Share of Population

Dependent Variable:	$\mathbb{1}$(Fintech)			
Sample of Borrowers:	All		Black	White
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Black-Owned)	0.159***	0.131***		
	(0.002)	(0.002)		
zipshare_black		0.125***	0.089***	0.078***
		(0.004)	(0.004)	(0.004)
Loan Amount FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes
Dep Var Mean	0.174	0.174	0.536	0.114
Observations	4,183,623	4,183,623	359,366	3,137,875

Note: This table reports estimates of a modified Equation 1, focusing on the role of the Black population in the borrower firm's neighborhood. Columns 2-4 include a continuous variable for the Black share of the population in a zip code. Columns 3-4 limit the sample to only Black-owned and White-owned businesses, respectively. We include state FE (indicators for each U.S. state and territory). Other controls are as described in Table 4. Standard errors are clustered by borrower zipcode. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.7: PPP Round Characteristics

	Round 1 N = 1,176,645		Round 2 (Early) N = 1,830,721		Round 2 (Late) N = 744,242		Round 3 N = 432,015	
	Mean	P50	Mean	P50	Mean	P50	Mean	P50
Lender Type								
Bank of America	0.6%		12.3%		4.2%		0.6%	
Citibank	0.4%		0.8%		0.3%		0.1%	
JPMC Bank	1.7%		9.3%		3.2%		1.8%	
Wells Fargo Bank	0.1%		6.3%		3.9%		1.7%	
Large Banks	11.5%		10.2%		7.1%		4.2%	
Medium Banks	37.9%		23.0%		13.1%		12.3%	
Small Banks	33.9%		17.1%		12.7%		44.6%	
Credit Union	3.4%		4.5%		4.9%		3.3%	
CDFI/Nonprofit	2.2%		1.5%		2.4%		2.3%	
Minority Dep Inst	4.2%		2.7%		1.9%		3.2%	
Fintech	4.0%		12.2%		46.3%		25.8%	
Borrower Firm Business Type								
Corporation	35.7%		32.5%		16.8%		5.5	
LLC	32.4%		29.0%		21.0%		12.1	
Non-Profit	4.2%		2.7%		1.5%		0.2	
Self-Employed	1.1%		5.5%		21.9%		19.5	
Sole Proprietorship	7.6%		16.5%		29.4%		55.6	
Subchapter S Corporation	18.3%		13.1%		9.2%		5.9	
Other	0.6%		0.6%		0.2%		1.2	
Borrower Firm Characteristics								
Employer Status	88.7%		68.0%		38.8%		17.8%	
Loan Amount ($)	200,471	58,600	68,394	20,833	29,148	13,344	21,010	15,650
Borrower Firm Industry								
Professional/Technical Services	12.8%		13.6%		13.5%		7.2%	
Ambulatory Health Care Services	8.5%		8.4%		6.5%		2.5%	
Food and Drinking Services	7.9%		5.7%		4.9%		3.1%	
Personal and Laundry Services	2.9%		5.3%		11.0%		8.4%	
Specialty Trade Contractors	6.6%		5.3%		4.7%		3.5%	
Other	61.2%		61.8%		59.5%		75.2%	
Borrower Firm Census Divisions								
East North Central	17.0%		13.3%		13.4%		17.6%	
East South Central	6.5%		4.4%		4.3%		6.6%	
Middle Atlantic	7.4%		9.7%		11.1%		5.9%	
Mountain	8.2%		7.7%		6.0%		5.1%	
New England	7.2%		5.4%		4.5%		2.5%	
Pacific	11.7%		20.8%		19.1%		8.6%	
South Atlantic	17.9%		21.9%		25.7%		14.1%	
West North Central	10.8%		5.7%		4.9%		27.8%	
West South Central	13.2%		11.2%		10.5%		11.7%	
Borrower Race/Ethnicity								
Share Black-Owned	2.1%		6.1%		19.9%		17.5%	
Share Hispanic/Latino-Owned	3.7%		8.1%		12.4%		7.1%	
Share Asian-Owned	5.9%		10.7%		11.3%		5.3%	
Share White-Owned	88.3%		75.2%		56.4%		70.1%	

Note: This table shows summary statistics of PPP borrowers across the various PPP rounds for the analysis sample. Round 1: 4/3/2020–4/16/2020; Round 2 Early: 4/27/2020–5/13/2020; Round 2 Late: 5/14/2020–8/9/2020; Round 3: 1/12/2021–2/23/2021. We highlight the distribution of the top-five 3-digit NAICS industry, and code the rest as "Other."

Table A.8: Black Business Ownership and PPP Lender Type by PPP Round

Dependent Variable:	$\mathbb{1}$(Fintech)			
PPP Round:	1	2 (Early)	2 (Late)	3
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Black-Owned)	0.025***	0.035***	0.087***	0.177***
	(0.002)	(0.001)	(0.002)	(0.003)
Loan Amount FE	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes
Dep Var Mean	0.040	0.122	0.461	0.257
Observations	1,181,767	1,846,203	747,991	436,060

Note: This table reports estimates of Equation 1, specifically replicating the specification in Table 4 column 8 for each PPP round. We distinguish Round 2 late from early (where early is intended to represent the initial rush) by defining early as ending on the last day on which there were at least 30,000 loans issued. The results are not sensitive to using an alternative threshold. Controls are as described in Table 4. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.9: Black Business Ownership and PPP Lender Type – Employer Firms Only

Panel A: Fintech PPP Loan

Dependent Variable:	$\mathbb{1}$(Fintech)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Black-Owned)	0.186***	0.165***	0.119***	0.142***	0.081***	0.080***	0.073***	0.075***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Loan Amount FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	No	No	Yes	No	Yes	Yes	No	Yes
Census Tract FE	No	No	No	Yes	No	No	No	No
Approval Week FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	No	Yes
Zip-by-Industry FE	No	No	No	No	No	No	Yes	No
Business Type FE	No	No	No	No	No	No	No	Yes
Dep Var Mean	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097
R^2	0.011	0.029	0.076	0.061	0.145	0.164	0.272	0.177
Observations	2,653,490	2,653,490	2,653,490	2,653,490	2,653,490	2,653,490	2,653,490	2,653,490

Panel B: Bank PPP Loan

Dependent Variable:	$\mathbb{1}$(Top 4 Bank)		$\mathbb{1}$(Large Bank)		$\mathbb{1}$(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Black-Owned)	0.036***	-0.008***	0.001	-0.018***	-0.235***	-0.056***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
Loan Amount FE	No	Yes	No	Yes	No	Yes
Zip Code FE	No	Yes	No	Yes	No	Yes
Approval Week FE	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes
Business Type FE	No	Yes	No	Yes	No	Yes
Dep Var Mean	0.184	0.184	0.114	0.114	0.517	0.517
R^2	0.000	0.335	0.000	0.139	0.006	0.346
Observations	2,653,490	2,653,490	2,653,490	2,653,490	2,653,490	2,653,490

Note: This table reports estimates of Equation 1 on the sample consisting of only employer firms. The dependent variable in Panel A is an indicator for whether the originating lender is fintech. Panel B repeats the specifications in columns 1 and 8 for indicators for whether the originating lender is a Top-4 bank (columns 1–2), large bank (columns 3–4), and small/medium-sized bank (columns 5-6). Control variables all pertain to the borrower firm and their particular PPP loan. Controls are as described in Table 4. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.10: Business Owner Race and PPP Lender Type – Excluding Fintech Lenders from Sample

Panel A: Bank PPP Loans to Black-Owned Businesses

Dependent Variable:	𝟙(PPP Lender is Checking Acct Bank)		𝟙(Top 4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Black-Owned)	-0.033***	-0.013**	0.059***	0.010***	0.008***	-0.019***	-0.142***	-0.022***
	(0.006)	(0.007)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Loan Amount FE	No	Yes	No	Yes	No	Yes	No	Yes
Zip Code FE	No	Yes	No	Yes	No	Yes	No	Yes
Approval Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Business Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Employer Status FE	No	Yes	No	Yes	No	Yes	No	Yes
Dep Var Mean	0.286	0.286	0.159	0.159	0.098	0.098	0.480	0.480
R^2	0.000	0.202	0.001	0.388	0.000	0.149	0.004	0.330
Observations	108,564	108,564	3,483,287	3,483,287	3,483,287	3,483,287	3,483,287	3,483,287

Panel B: Bank PPP Loans to White-Owned Businesses

Dependent Variable:	𝟙(PPP Lender is Checking Acct Bank)		𝟙(Top 4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(White-Owned)	0.011***	0.010**	-0.155***	-0.023***	-0.013***	-0.017***	0.235***	0.073***
	(0.004)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Loan Amount FE	No	Yes	No	Yes	No	Yes	No	Yes
Zip Code FE	No	Yes	No	Yes	No	Yes	No	Yes
Approval Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Business Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Employer Status FE	No	Yes	No	Yes	No	Yes	No	Yes
Dep Var Mean	0.286	0.286	0.159	0.159	0.098	0.098	0.480	0.480
R^2	0.000	0.202	0.025	0.388	0.000	0.150	0.036	0.333
Observations	108,564	108,564	3,483,287	3,483,287	3,483,287	3,483,287	3,483,287	3,483,287

Note: This table reports estimates of Equation 1 on the sample excluding PPP loans from fintech lenders. The independent variable in Panel A is an indicator for whether the borrower is a Black-owned business. The independent variable in Panel B is an indicator for whether the borrower is a White-owned business. In both panels, the dependent variables are indicators for whether the originating lender is the borrower's checking account bank (columns 1–2), Top-4 bank (columns 3–4), large bank (columns 5–6), and small/medium-sized bank (columns 7–8). Control variables all pertain to the borrower firm and their particular PPP loan. Loan Amount FE are 100 indicator variables for each percentile of the loan size distribution. Zip Code FE are indicators for each zip code. Approval Week FE are indicators for the week in which the PPP loan was approved by SBA. Industry FE are 104 indicators for NAICS 3-digit classifications that appear in the data. Business type FE are 7 indicators for the firm's business type (see Table 3). Employer status is an indicator for whether the firm has at least one employee. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.11: Other Race Business Ownership & PPP Lender Type (Bank & Credit Relationship Controls)

Panel A: Fintech PPP Loan

Dependent variable:			𝟙(Fintech)		
	(1)	(2)	(3)	(4)	(5)
𝟙(Asian-Owned)	-0.066***	-0.070***	-0.070***	-0.068***	-0.050***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
𝟙(Hispanic-Owned)	-0.041***	-0.037***	-0.038***	-0.037***	-0.021***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
𝟙(White-Owned)	-0.057***	-0.058***	-0.059***	-0.057***	-0.041***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
𝟙(Credit from Fintech)			0.075***	0.078***	0.109***
			(0.003)	(0.003)	(0.005)
𝟙(Credit from Conv.)			-0.012***	-0.011***	-0.015***
			(0.003)	(0.003)	(0.004)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes
Months Since Statement FE	No	Yes	Yes	Yes	Yes
Checking Acct Bank FE	No	Yes	Yes	Yes	Yes
Monthly Cash Inflow FE	No	No	No	Yes	Yes
Monthly Net Cash Inflow FE	No	No	No	Yes	Yes
Bank Statement Sample	Latest	Latest	Latest	Latest	Latest within 6 months
Dep Var Mean	0.363	0.363	0.363	0.363	0.424
Observations	168,360	168,360	168,360	168,360	91,870

Panel B: Bank PPP Loan

Dependent Variable:	𝟙(PPP Lender is) Checking Acct Bank		𝟙(Top 4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Asian-Owned)	-0.007	-0.010**	0.003	0.005	0.014***	0.018***	0.014***	0.013***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)
𝟙(Hispanic-Owned)	0.028***	0.021***	0.008*	0.003	0.011***	0.015***	0.025***	0.019***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
𝟙(White-Owned)	0.020***	0.012***	-0.010***	-0.002	0.019***	0.020***	0.060***	0.046***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
𝟙(Credit from Fintech)		-0.040***		-0.025***		-0.011***		-0.035***
		(0.004)		(0.003)		(0.002)		(0.003)
𝟙(Credit from Conv.)		0.011***		0.001		0.005**		-0.002
		(0.003)		(0.002)		(0.002)		(0.003)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Months Since Statement FE	No	Yes	No	Yes	No	Yes	No	Yes
Checking Acct Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Monthly Cash Inflow FE	No	Yes	No	Yes	No	Yes	No	Yes
Monthly Net Cash Inflow FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank Statement Sample	Latest	Latest	Latest	Latest	Latest	Latest	Latest	Latest
Dep Var Mean	0.274	0.274	0.177	0.177	0.090	0.090	0.295	0.295
Observations	168,360	168,360	168,360	168,360	168,360	168,360	168,360	168,360

Note: This table reports estimates of a modified Equation 1, focusing on the role of bank and credit relationships and using indicators for the three other races/ethnicities. The sample is restricted to those matched to bank statement data. In all columns except for Panel A Column 5, we include only information from a firm's latest statement prior to the loan approval. Panel A Column 5 includes only the latest statement if it is within six months of loan approval. The dependent variable in Panel A is an indicator for whether a PPP loan is originated by a fintech lender. The dependent variables in Panel B are indicators for whether the originating lender is the borrower's checking account bank (columns 1–2), Top-4 bank (columns 3–4), large bank (columns 5–6), and small/medium-sized bank (columns 7–8). We report coefficients on indicators for whether the borrower has previous credit relationships with fintech and non-fintech lenders. Controls are as described in Table 6. Standard errors are clustered by borrower zipcode. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.12: Self-Reported Business Owner Race and PPP Lender Type

Panel A: Fintech PPP Loan

Dependent Variable:	$\mathbb{1}$(Fintech)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(SelfID Black-Owned)	0.507***	0.414***	0.314***	0.344***	0.222***	0.201***	0.192***	0.186***
	(0.006)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Loan Amount FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	No	No	Yes	No	Yes	Yes	No	Yes
Census Tract FE	No	No	No	Yes	No	No	No	No
Approval Week FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	No	Yes
Zip-by-Industry FE	No	No	No	No	No	No	Yes	No
Business Type FE	No	No	No	No	No	No	No	Yes
Employer Status FE	No	No	No	No	No	No	No	Yes
Dep Var Mean	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173
R^2	0.181	0.239	0.335	0.294	0.417	0.437	0.556	0.459
Observations	1,098,682	1,098,682	1,098,682	1,098,682	1,098,682	1,098,682	1,098,682	1,098,682

Panel B: Bank PPP Loan

Dependent Variable:	$\mathbb{1}$(Top 4 Bank)		$\mathbb{1}$(Large Bank)		$\mathbb{1}$(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(SelfID Black-Owned)	-0.041***	-0.013***	-0.043***	-0.028***	-0.380***	-0.128***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)
Loan Amount FE	No	Yes	No	Yes	No	Yes
Zip Code FE	No	Yes	No	Yes	No	Yes
Approval Week FE	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes
Business Type FE	No	Yes	No	Yes	No	Yes
Employer Status FE	No	Yes	No	Yes	No	Yes
Dep Var Mean	0.136	0.136	0.090	0.090	0.485	0.485
R^2	0.001	0.341	0.002	0.197	0.058	0.436
Observations	1,098,682	1,098,682	1,098,682	1,098,682	1,098,682	1,098,682

Panel C: Other Races

Dependent Variable:	$\mathbb{1}$(Fintech)		$\mathbb{1}$(Top 4 Bank)		$\mathbb{1}$(Large Bank)		$\mathbb{1}$(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(SelfID Asian-Owned)	-0.409***	-0.160***	0.165***	0.039***	0.037***	0.015***	0.123***	0.041***
	(0.006)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.006)	(0.003)
$\mathbb{1}$(SelfID Hispanic-Owned)	-0.349***	-0.124***	0.087***	0.009***	0.023***	0.031***	0.112***	0.069***
	(0.007)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.005)	(0.002)
$\mathbb{1}$(SelfID White-Owned)	-0.523***	-0.189***	0.015***	0.009***	0.049***	0.028***	0.449***	0.149***
	(0.006)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)
Loan Amount FE	No	Yes	No	Yes	No	Yes	No	Yes
Zip Code FE	No	Yes	No	Yes	No	Yes	No	Yes
Approval Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Business Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Employer Status FE	No	Yes	No	Yes	No	Yes	No	Yes
Dep Var Mean	0.173	0.173	0.136	0.136	0.090	0.090	0.485	0.485
R^2	0.199	0.460	0.025	0.342	0.003	0.197	0.131	0.439
Observations	1,098,682	1,098,682	1,098,682	1,098,682	1,098,682	1,098,682	1,098,682	1,098,682

Note: This table reports estimates of Equation 1. The independent variables are the self-reported race/ethnicity of the borrower, and the sample is restricted to the subset of loans for which race/ethnicity is self-reported. Note that in the main analysis, we use only predicted race (self-reported race is used to train the random forest algorithm, but does not replace the prediction for self-reported observations). The dependent variable in Panel A is an indicator for whether the originating lender is fintech. Panel B repeats the specifications in columns 1 and 8 for indicators for whether the originating lender is the borrower's checking account bank (columns 1–2), a Top-4 bank (columns 3–4), large bank (columns 5–6), and small/medium-sized bank (columns 7–8). Panel C repeats Panel B, but adds two columns for fintech loans and considers the other three race/ethnicities. Here, Black-owned businesses represent the single omitted group, so the coefficients should be interpreted relative to them. Control variables all pertain to the borrower firm and their particular PPP loan. Loan Amount FE are 100 indicator variables for each percentile of the loan size distribution. Zip Code and Census Tract FE are indicators for each zip code and census tract. Approval Week FE are indicators for the week in which the PPP loan was approved by SBA. Industry FE are 104 indicators for NAICS 3-digit classifications that appear in the data. Business type FE are 7 indicators for the firm's business type (see Table 3). Employer status is an indicator for whether the firm has at least one employee. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.13: Business Owner Race and PPP Lender Type with Bank and Credit Relationship Controls (Excl. Fintech Lenders from Sample)

Panel B: Bank PPP Loans to Black-Owned Businesses

Dependent Variable:	𝟙(PPP Lender is) Checking Acct Bank		𝟙(Top 4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Black-Owned)	-0.010	0.000	0.008	0.005	-0.010**	-0.015***	-0.037***	-0.024***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
𝟙(Credit from Fintech)		-0.001		0.007*		0.000		-0.007*
		(0.005)		(0.004)		(0.003)		(0.004)
𝟙(Credit from Conv.)		0.008*		-0.000		0.006*		-0.012***
		(0.005)		(0.003)		(0.003)		(0.004)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Months Since Statement FE	No	Yes	No	Yes	No	Yes	No	Yes
Checking Acct Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Monthly Cash Inflow FE	No	Yes	No	Yes	No	Yes	No	Yes
Monthly Net Cash Inflow FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank Statement Sample	Latest	Latest	Latest	Latest	Latest	Latest	Latest	Latest
Dep Var Mean	0.430	0.430	0.278	0.278	0.141	0.141	0.464	0.464
Observations	168,360	168,360	168,360	168,360	168,360	168,360	168,360	168,360

Panel B: Bank PPP Loans to White-Owned Businesses

Dependent Variable:	𝟙(PPP Lender is) Checking Acct Bank		𝟙(Top 4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Asian-Owned)	-0.032***	-0.037***	-0.002	-0.005	0.005	0.012**	-0.019**	-0.020***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.008)	(0.008)
𝟙(Hispanic-Owned)	0.037***	0.027***	0.016**	0.008	0.006	0.011*	0.013	0.010
	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.008)	(0.007)
𝟙(White-Owned)	0.013*	0.001	-0.013**	-0.007	0.012**	0.016***	0.052***	0.035***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)
𝟙(Credit from Fintech)		-0.001		0.007*		0.000		-0.008*
		(0.005)		(0.004)		(0.003)		(0.004)
𝟙(Credit from Conv.)		0.007		-0.001		0.006*		-0.012***
		(0.005)		(0.003)		(0.003)		(0.004)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Months Since Statement FE	No	Yes	No	Yes	No	Yes	No	Yes
Checking Acct Bank FE	No	Yes	No	Yes	No	Yes	No	Yes
Monthly Cash Inflow FE	No	Yes	No	Yes	No	Yes	No	Yes
Monthly Net Cash Inflow FE	No	Yes	No	Yes	No	Yes	No	Yes
Bank Statement Sample	Latest	Latest	Latest	Latest	Latest	Latest	Latest	Latest
Dep Var Mean	0.430	0.430	0.278	0.278	0.141	0.141	0.464	0.464
Observations	168,360	168,360	168,360	168,360	168,360	168,360	168,360	168,360

Note: This table reports estimates of Equation 1 on the Ocrolus bank statement matched sample excluding PPP loans from fintech lenders. The independent variable in Panel A is an indicator for whether the borrower is a Black-owned business. The independent variable in Panel B is an indicator for whether the borrower is a White-owned business. In both panels, the dependent variables are indicators for whether the originating lender is the borrower's checking account bank (columns 1–2), Top-4 bank (columns 3–4), large bank (columns 5–6), and small/medium-sized bank (columns 7–8). Control variables all pertain to the borrower firm and their particular PPP loan. Controls are as described in Table 6. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.14: How Race Predicts Fintech with Card Revenue Controls within Approval Month

Dependent variable:	𝟙(Fintech)		Banks: 𝟙(Top 4)		𝟙(Large)		𝟙(Small/Med)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Black-Owned)	0.024***	0.015***	0.013***	0.014***	-0.011***	-0.011***	-0.012***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Card Revenue At Approval FE	No	Yes	No	Yes	No	Yes	No	Yes
Dep Var Mean	0.097	0.097	0.179	0.179	0.122	0.122	0.515	0.515
Observations	582,099	582,099	582,099	582,099	582,099	582,099	582,099	582,099

Note: This table reports estimates of a modified Equation 1, focusing on the role of firm revenue during the PPP loan approval month. The sample is restricted to those matched to Enigma data on credit and debit card transactions. Controls are as described in Table 8. Standard errors are clustered by borrower zipcode. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.15: Black Business Ownership and Fintech PPP Loans Mediated by Racial Animus (Bank Statement-Matched Sample)

Panel A: Fintech PPP Loans as Dependent Variable

Dependent variable:	$\mathbb{1}$(Fintech)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}$(Black-Owned)	0.059***	0.060***	0.058***	0.057***	0.059***	0.058***	0.052***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\mathbb{1}$(Black-Owned) $\times$ Racial Animus		0.013***	0.011*	0.022***	0.023***	0.004	0.016***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Racial Animus Measure		Stephens-Davidowitz	Nationscape	IAT (Implicit)	IAT (Explicit)	Segregation (Dissimilarity)	Segregation (Isolation)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Checking Acct Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Months Since Statement FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Cash Inflow FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Net Cash Inflow FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.361	0.361	0.361	0.361	0.361	0.361	0.361
Observations	169,818	169,818	169,818	169,818	169,818	169,818	169,818

Panel B: Top-4 Bank PPP Loans as Dependent Variable

Dependent variable:	$\mathbb{1}$(Top 4)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}$(Black-Owned)	0.001	0.000	0.001	0.000	0.001	0.001	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\mathbb{1}$(Black-Owned) $\times$ Racial Animus		0.012^{***}	0.003	0.009^{**}	0.007^{*}	0.002	0.008^{**}
		(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Racial Animus Measure		Stephens-Davidowitz	Nationscape	IAT (Implicit)	IAT (Explicit)	Segregation (Dissimilarity)	Segregation (Isolation)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Checking Acct Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Months Since Statement FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Cash Inflow FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Net Cash Inflow FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.176	0.176	0.176	0.176	0.176	0.176	0.176
Observations	169,818	169,818	169,818	169,818	169,818	169,818	169,818

Panel C: Non-Top 4 Bank PPP Loans as Dependent Variable

Dependent variable:				$\mathbb{1}$(Non-Top 4 Bank)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}$(Black-Owned)	-0.061***	-0.062***	-0.061***	-0.060***	-0.061***	-0.060***	-0.050***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\mathbb{1}$(Black-Owned) $\times$ Racial Animus		-0.016***	-0.014***	-0.026***	-0.027***	-0.014***	-0.029***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Racial Animus Measure		Stephens-Davidowitz	Nationscape	IAT (Implicit)	IAT (Explicit)	Segregation (Dissimilarity)	Segregation (Isolation)
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer Status FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Checking Acct Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Months Since Statement FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Cash Inflow FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Net Cash Inflow FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.389	0.389	0.389	0.389	0.389	0.389	0.389
Observations	169,818	169,818	169,818	169,818	169,818	169,818	169,818

Note: This table repeats Table 10 but within the bank statement-matched (Ocrolus) sample. It reports estimates of a modified Equation 1, focusing on the interaction between the indicator for Black-owned business and a standardized measure of racial animus in the borrower location. The dependent variable differs across the three panels: In Panel A, it is an indicator for a fintech PPP loan, in Panel B, it is an indicator for a Top-4 bank PPP loan, and in Panel C, it is an indicator for a non-Top 4 bank PPP loan. In each panel, column 1 includes the same controls as the specification in Table 4 Panel A column 8. The racial animus measures are as follows: column 2 uses the number of racially charged searches in a designated media market (DMA); column 3 uses responses to the question on favorability toward Black people in the Nationscape survey aggregated to the congressional district level; columns 4–5 use the implicit and explicit score from the Implicit Association Test (IAT) aggregated to the county level; columns 6–7 use the dissimilarity and isolation index at the metropolitan statistical area (MSA) level. All racial animus measures are standardized at their respective levels of geography, weighted by the number of PPP loans. Controls are as described in Tables 4 and 6. Standard errors are clustered by zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.16: Summary Statistics on Automation during PPP among Small Banks

	Automating Banks N = 74,965	Never-Automated Banks N = 1,949,709	p-value
Unique Banks	20	3,870	
Share Loans After Automation	0.531		
Assets (Million $)	28,408	11,129	0.000
Asian-Owned Share Before Automation	0.064	0.055	0.000
Asian-Owned Share After Automation	0.070	0.055	0.000
Black-Owned Share Before Automation	0.041	0.035	0.000
Black-Owned Share After Automation	0.112	0.035	0.000
Hispanic-Owned Share Before Automation	0.058	0.042	0.000
Hispanic-Owned Share After Automation	0.073	0.042	0.000
White-Owned Share Before Automation	0.837	0.868	0.000
White-Owned Share After Automation	0.746	0.868	0.000

Note: This table contains summary statistics of the sample used in the automation analysis. It compares small banks that automated (left column) to those that did not (right column), and reports the p-value of a t-test comparing the difference of the two means.

Table A.17: Automation during PPP and Lending to Black-Owned Small Businesses

Dependent Variable:	$\mathbb{1}$(Black-Owned)			
	(1)	(2)	(3)	(4)
$\mathbb{1}$(After Automation)	0.060***	0.043***	0.060***	0.043***
	(0.011)	(0.006)	(0.013)	(0.007)
Level of Clustering	Bank	Bank	Bank-Week	Bank-Week
Bank FE	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes
Loan Amount FE	No	Yes	Yes	No
Zip Code FE	No	Yes	Yes	No
Industry FE	No	Yes	Yes	No
Business Type FE	No	Yes	Yes	No
Employer Status FE	No	Yes	Yes	No
Dep Var Mean	0.037	0.037	0.037	0.037
Observations	2,024,674	2,024,674	2,024,674	2,024,674

Note: This table reports estimates of Equation 2, but adjusts the clustering of standard errors. It shows the effect of automation on the chances a loan is to a Black-owned businesses. Standard errors are clustered by bank in columns 1-2, and double clustered by bank and week approved in columns 3-4. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.18: Unsealed DOJ PPP Fraud Cases by Lender Type and Race

	N	Mean
Black	191	8.4%
Fintech	268	46.3%
Small Bank	268	23.9%
Top Bank	268	13.4%

Note: This table reports statistics on unsealed DOJ PPP fraud cases as of November 15, 2021 that we matched to companies in our loan sample (the sample from Table 1 Panel B). We report the share where we have identified the owner to be Black-owned, which is restricted to the sample from Table 2 Panel A, and thus has a smaller sample. We also report the share of these loans originated by small banks, top banks, and fintechs.

A Supplemental Details on Racial Animus Measures

This appendix describes the construction of our six measures of racial animus.

A.1 Stephens-Davidowitz (2013) Measure

This measure uses Google search data to proxy for social attitudes. Stephens-Davidowitz (2013) defines racial animus using the search rate of a racially charged word in a designated media market (DMA) from 2004 to 2007. He defines the racially charged search rate in a DMA j as

$$\text{Racially Charged Search Rate}_j = \frac{\left[\frac{\text{Google searches including the word “Word(s)”}}{\text{Total Google searches}}\right]_j}{\left[\frac{\text{Google Searches including the word “Word(s)”}}{\text{Total Google searches}}\right]_{\max}}. \tag{4}$$

Figure A.9 Panel A shows the geographical distribution of racially charged searches by DMA, and Figure A.10 Panel A shows the distribution of racially charged searches by DMA.

A.2 Nationscape Survey

Nationscape is a large public opinion survey conducted in the lead-up to the 2020 elections (see Tausanovitch and Vavreck, 2020). To capture racial bias, we follow Bursztyn et al. (2021) in using responses to the question: ”Here are the names of some groups that are in the news from time to time. How favorable is your impression of each group or haven’t you heard enough to say? — Blacks.” The scale is from 1 to 4, with 1 being very favorable and 4 being very unfavorable. We keep only the White respondents. Figure A.9 Panel B maps the geographical distribution of the average response by congressional district, the finest geographic level available. We treat the response ”Haven’t heard enough” as missing. Figure A.10, Panel B shows the distribution of individual responses to the question by White respondents.

A.3 Project Implicit IAT Score

Project Implicit runs the Implicit Association Tests (IATs). In particular, we use data from the Race IAT, which measures explicit and implicit bias against different races (Xu et al., 2014). We keep only responses from White, non-Hispanic respondents.

Implicit bias is measured by asking respondents to first use two buttons (“E” or “I”) on their keyboard to identify a series of faces that flash on the screen as Black or White and then a series of words that flash on the screen as good or bad. In the following rounds, both faces and words will flash on the screen, but the respondents will still be limited to “E” or “I” — only “E” could now mean “Black or good” while “I” will mean “White or bad” in one round, and later be reversed so “E” means “Black or bad” and “I” means “White or good” in the next round. The idea behind the IAT is that a slower reaction to selecting “good” when “Black” is linked to it or “bad” when “White” is linked to it implies an implicit bias against Black people or bias in favor of White people (see Lopez, 2017, for more details). The IAT score is then calculated as the average difference in average speed per participant between each corresponding “actual” and practice block scaled by the pooled standard deviation.

Figure A.9 Panel C shows the geographical distribution of average IAT scores by county. We omit counties with fewer than 50 respondents. Figure A.10 Panel C shows the distribution of the IAT score at the respondent level.

A.4 Project Implicit IAT Explicit Attitude

Following the IAT, respondents are asked to take a follow-up survey. We follow Bursztyn et al. (2021) in using the first question in the survey to proxy for explicit attitudes: “Please rate how warm or cold you feel toward the following groups (0 = coldest feelings, 5 = neutral, 10 = warmest feelings): African Americans.” The responses are on a scale from 0 to 10.

Figures A.10 Panel D and A.9 Panel D show the response distribution and geographical distribution of the explicit score, respectively. We omit counties with fewer than 50 respondents.

A.5 Dissimilarity Index

As an alternative to surveys to measuring racial bias, we also estimated residential segregation at the metropolitan statistical area (MSA) level to proxy for racial bias. Among many other things, residential segregation could represent a certain revealed preference of the residents.

The residential segregation literature proposes various different methods of measuring segregation. Here, we consider the dissimilarity index, which measures how similar the distribution of Black residents in a tract is relative to the distribution of White residents in the same tract (Massey and Denton, 1988):

$$D_T = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{w_i}{W_T} - \frac{b_i}{B_T}\right| \tag{5}$$

where b_i and w_i correspond to the share of Black and White people in tract i, respectively, and b_T and w_T correspond to the same shares in MSA T. The higher the index, the more segregated an MSA is. Figure A.10 Panel E shows the distribution of the dissimilarity index. Figure A.9 Panel E maps MSA-level residential segregation across the U.S.

A.6 Isolation Index

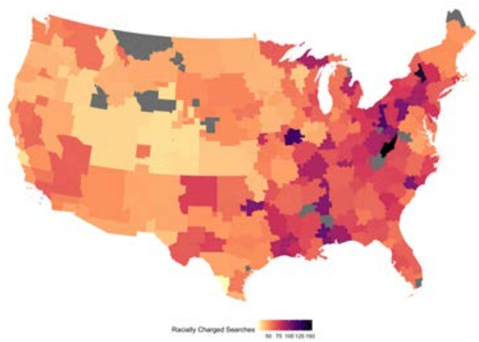
We estimate an additional measure of residential segregation: the isolation index. Isolation measures the extent to which Black people only interact with other Black people, instead of other White people (Massey and Denton, 1988):

$$I_T = \sum_{i=1}^{N}\left(\frac{b_i}{B_T} \times \frac{b_i}{b_i + w_i}\right) \tag{6}$$

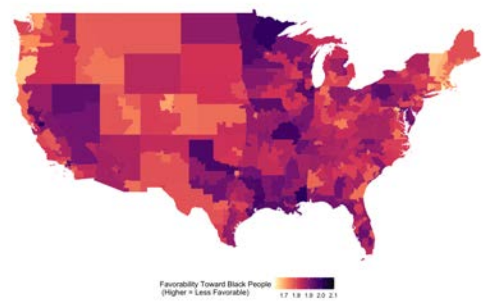
with variables defined as above. As Black residents are more isolated, the isolation index approaches one. Note that the isolation index measures a different dimension of segregation compared to the dissimilarity index. The dissimilarity index does not consider the relative size of the groups being compared. For example, a particular MSA might be “even” according to the dissimilarity index, but if the population of Black residents is much smaller than that of White residents, then the MSA will be high on the isolation index. Figure A.10 Panel F shows the distribution of the isolation index. Figure A.9 Panel F maps the geography of isolation.

Figure A.9: **Geographical Distribution of Racial Animus**

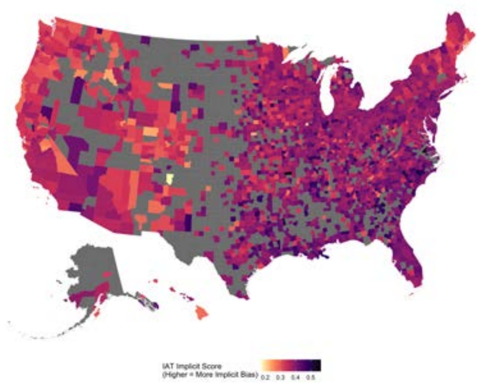
(A) Racially Charged Searches



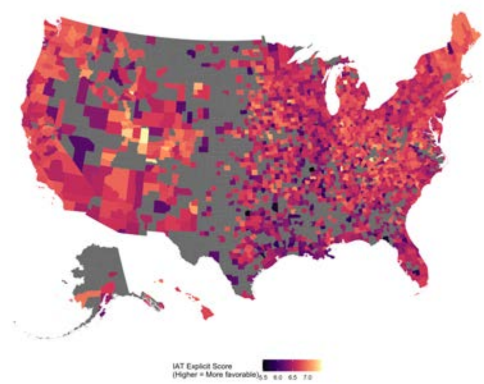
(B) Nationscape Survey



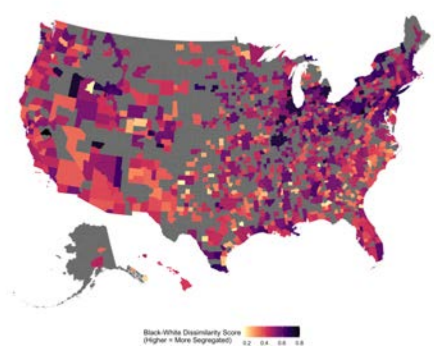
(C) IAT Implicit Scores



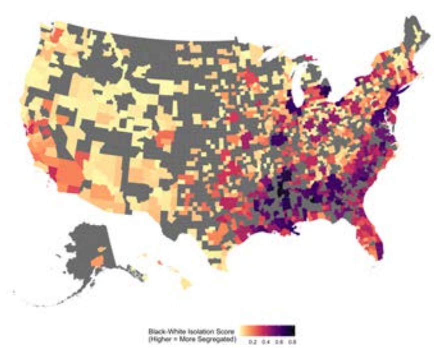
(D) IAT Explicit Scores



(E) Dissimilarity Index



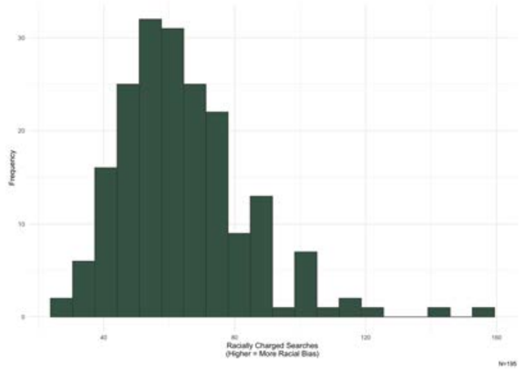
(F) Isolation Index



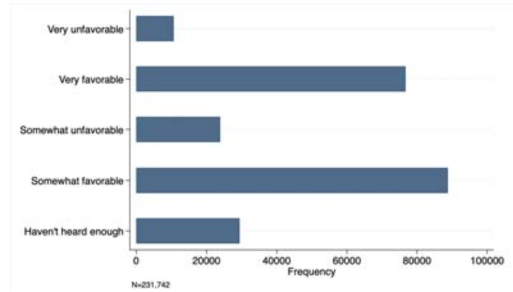
Note: This figure shows the geographical distribution of each proxy of racial bias used in the analysis. Racially charged searches (Panel A) are at the designated media market (DMA) level, plotted at the county level. IAT scores (Panels B and C) are aggregated at the county level; counties with less than 50 respondents are coded as omitted. Nationscape surveys (Panel D) are aggregated at the congressional district level. The dissimilarity and isolation index (Panels E and F) are calculated at the metro/micropolitan statistical area (MSA) level.

Figure A.10: **Distribution of Racial Animus**

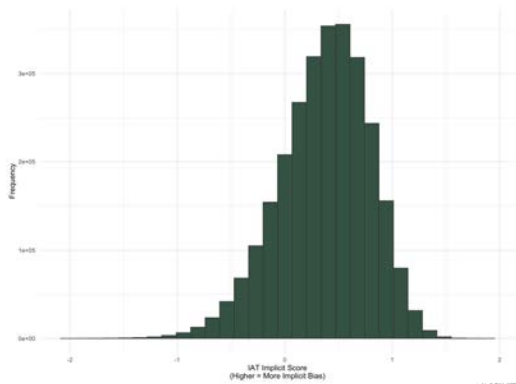
(A) Racially Charged Searches



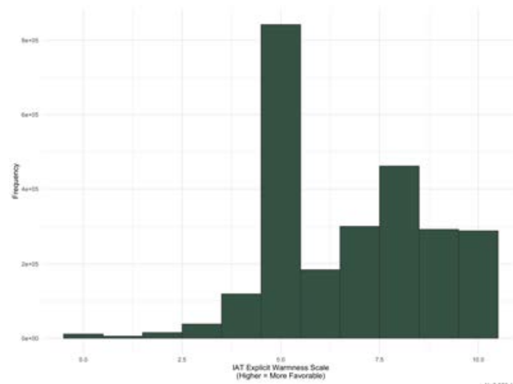
(B) Nationscape Survey



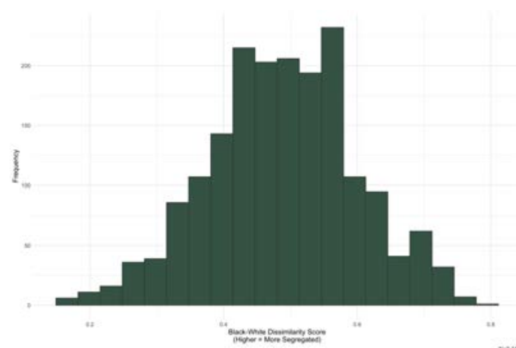
(C) IAT Implicit Scores



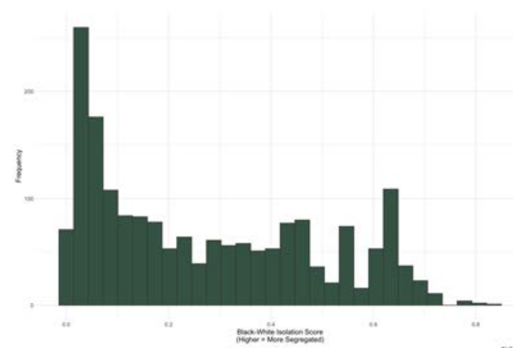
(D) IAT Explicit Scores



(E) Dissimilarity Index



(F) Isolation Index



Note: This figure shows the distribution of each proxy of racial bias used in the analysis. Racially charged searches (Panel A) are at the designated media market (DMA) level. IAT scores (Panels B and C) are at the respondent level. Nationscape surveys (Panel D) are at the respondent level. The dissimilarity and isolation index (Panels E and F) are calculated at the metro/micropolitan statistical area (MSA) level.