Lender Automation and Racial Disparities in Credit Access

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Abstract

Process automation reduces racial disparities in credit access through enabling smaller loans, broadening banks' geographic reach, and removing human biases from decision-making. We document these findings in the context of the Paycheck Protection Program (PPP), a setting where private lenders faced no credit risk but decided which firms to serve. Black-owned firms primarily obtained PPP loans from automated fintech lenders, especially in areas with high racial animus. After traditional banks automated their loan processing procedures, their PPP lending to Black-owned firms increased. Our findings cannot be fully explained by racial differences in loan application behaviors, pre-existing banking relationships, firm performance, or fraud rates.

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Researchers and policy makers in the U.S. and elsewhere have long been concerned about racial disparities in access to financial services (Crutsinger, 2021; Abrams, 2021; Crowell, 2021). The recent emergence of fintech lenders has raised new and important questions about how their technologies—notably algorithmic underwriting and process automation—might affect racial disparities in lending. Much of the resulting literature has focused on the effects of algorithmic underwriting practices on racial disparities in credit access (Blattner et al., 2021; Bartlett et al., 2021; Fuster et al., 2022). In this paper, we study the role of process automation separately from that of algorithmic underwriting, and show that automating processes such as income and payroll verification can substantially reduce racial disparities in small business lending.

We explore three possible channels for this finding. First, since automated lenders have lower fixed costs per loan, they can serve smaller businesses, which are more likely to be minority-owned. Second, automation generally goes hand-in-hand with online loan origination procedures. This allows automated lenders to more easily serve customers in regions with higher minority shares that are traditionally underserved by the branch networks of less automated lenders. Third, automation reduces human influence on decisions such as the order in which to process loans when facing capacity constraints, and can thus mitigate racial discrimination—whether of the taste-based or statistical variety—in lending. Using an array of novel datasets, we show that automation appears to reduce racial disparities in small business lending through all three channels, including through an economically important reduction in discrimination.

One challenge to understanding the determinants of racial disparities in credit markets is the need to disentangle the independent role of race from other factors, such as differences in credit risk, that might be correlated with race while also directly influencing credit outcomes. To overcome these challenges, we study small business lending in an important setting with no role for confounding factors such as credit risk and selection on contract terms. Our setting is the Paycheck Protection Program (PPP), which was established by the CARES Act in March 2020 to help small businesses struggling during the COVID-19 pandemic. With more than $800 billion in loans, it is one of the largest single public finance programs in U.S. history. Three features make the PPP a promising setting to study racial disparities in small business lending.

First, PPP loan size was set as a fixed percentage of payroll, and there was no variation in other contract terms. Second, PPP loan distribution occurred via private lenders, which were compensated with a fixed share of the loan amount. Most lenders originated PPP loans using processes designed for pre-existing small business lending volume. When confronted with 100 or 1,000 times the normal application volumes, lenders faced severe capacity constraints, forcing them to prioritize among applicants (Morel et al., 2021; Zhou, 2020; Flitter and Cowley, 2020). The Small Business Administration (SBA) did not issue specific guidance on loan distribution, leaving the private lenders to independently determine which businesses to serve given the fee structure and other factors such as lender cost structure or processing capacity. Third, PPP loans were 100% guaranteed by the federal government, so the originating lenders had no financial exposure to the borrower's performance. Consequently, any observed racial disparities in lending should not reflect differences in expected interest revenues or loan losses. Studying a setting with no credit risk also allows us to isolate the role of process automation (e.g., automating application intake and payroll verification) from the role of algorithmic underwriting (e.g., predicting default risk using machine learning), which has been the focus of much of the related research in financial economics.

We work with public administrative data from the SBA on 11.8 million PPP loans made between April 3, 2020, and May 31, 2021. We restrict the sample to "first draw" loans made before February 24, 2021, when program rules were changed to explicitly prioritize lending to small firms and minority-owned businesses. In a first step, we build on a well-established literature to predict the race or ethnicity of the owners of PPP-funded businesses based on the owners' names and locations (Imai and Khanna, 2016; Humphries et al., 2019; Tzioumis, 2018). After collecting owner names from business registrations in collaboration with the data analytics firm Middesk, we assign race and ethnicity to the business owners for 4.2 million PPP loans. This predicted race based on signals provided by name and location is particularly relevant in our context, since loan officers typically observe those characteristics but do not know borrowers' actual race. However, our results are robust to using only the subsample of PPP borrowers with information on self-identified race.

Our approach to establishing the effect of automation on racial disparities in small business lending uses two sets of comparisons. First, we study the rates of lending to minority-owned businesses across lender types with different degrees of automation, with a particular focus on fintech firms as the lenders with the most automated lending systems, and small banks as those with the least automated systems. (We use data on bank branch-level software spending to show that automation generally increases in bank size.) Second, we analyze within-lender changes in PPP lending to minority-owned businesses in a subset of traditional lenders which automated their loan origination processes during the PPP period. Across both types of analyses, we show that lenders with more automated loan processing systems were more likely to extend PPP loans to minority-owned firms. Our evidence suggests this happens partly because lenders with more automated systems can make smaller loans and loans in higher-minority areas, and partly because automated loan processing reduces the scope for human biases to lead to discrimination of minority-owned firms. Data from a subset of PPP loan applications provides evidence that racial differences in loan approval rates at conventional lenders (but not at fintechs) contributes to the observed across-lender patterns.

We first document variation across types of financial institutions in the unconditional propensity to extend PPP loans to businesses owned by different races. Fintech lenders with the most automated lending systems made 26.5% of their PPP loans to Black-owned businesses. Among traditional banks, PPP loan shares to Black-owned businesses increased with bank size, ranging from 3.3% at small banks to 6.2% at the largest four banks (Wells Fargo, Bank of America, JPMorgan Chase, and Citibank). We also show that bank branches with more automation, as measured by software spending, lend more to Black-owned firms. 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. There are also some smaller differences across lenders in the propensity to lend to White-, Asian-, and Hispanic-owned firms. However, the differences in lending to Black-owned businesses across different lender types are much more dramatic, so we focus our paper on understanding this disparity.

To directly test whether automating the loan origination process increases PPP lending to Black-owned businesses, we analyze lending at a number of smaller banks that automated during the PPP period by outsourcing the back-end processing of their PPP loan applications to a third-party software provider. In an event study differences-in-differences analysis, we find that relative to other comparable banks that did not automate their processes, automation increased the automating banks' shares of PPP loans to Black-owned businesses by 6 percentage points, relative to a pre-automation share of 4.4%.

We next explore why automation might increase lending to Black-owned businesses. We first focus on automated lenders' ability to make smaller loans and originate loans without relying on a branch network.

The compensation structure for originating PPP loans included payments to banks that were increasing in loan size (and thus mechanically also increasing in firm size). The lower cost structure and higher processing capacity of automated lenders could thus allow them to originate smaller PPP loans, which were disproportionately granted to Black-owned businesses. Second, traditional lenders may be more likely to serve borrowers in areas where the lenders have a physical presence. Fintech lenders might thus disproportionately serve firms in underbanked areas—firms that are more likely to be Black-owned.

We assess the role of these factors by including tight controls for loan size and firm location (as well as other firm characteristics such as industry, employer status, and business form). Before controlling for firm characteristics, Black-owned firms are 26 percentage points more likely to obtain a fintech PPP loan than firms owned by individuals of another race, compared to a baseline probability across all firms of getting a fintech loan of 17.4 percent. Including controls for firm characteristics reduces this difference to 12.1 percentage points. Similarly, Black-owned firms are unconditionally 30 percentage points less likely to obtain their PPP loan from a small bank (relative to a baseline probability of getting a PPP loan from such a lender of 48.2%), a gap that falls to 8.1 percentage points after controlling for firm characteristics. In addition to this across-lender analysis, we show that firm characteristics also explain part of the causal within-bank effect of automation. However, even with granular controls for loan and firm characteristics, the effect is 4.3 percentage points, which represents nearly a doubling of the pre-automation Black-owned share.

Overall, these findings indicate that a substantial part of the unconditional racial disparities in PPP lender identity is driven by more automated lenders, and in particular fintech lenders, making smaller PPP loans and serving borrowers in geographic areas underserved by traditional lenders. However, even after conditioning on firm characteristics and focusing on an environment like the PPP with no credit risk, lending rates to Black-owned firms are substantially higher at more automated lenders, and increase within lender after automating the loan origination process. These findings raise the possibility that an additional channel for automation to reduce racial disparities in small business lending is by mitigating racial discrimination. In credit markets, such discrimination can generally take two forms. Statistical discrimination describes decision-makers using race as a proxy for unobserved credit risk. Preference-based discrimination arises when decision-makers systematically dislike (and thus disadvantage) members of a certain race. While both forms of discrimination are illegal in the U.S., preference-based discrimination has particular ethical and regulatory implications. The PPP offers a unique setting in which private lenders face no credit risk, implying no reason for statistical discrimination in either human or algorithmic lending decisions. If evidence for racial discrimination can be found, it is thus most likely preference-based.

To explore this possibility, we test whether the conditional disparity in lending to Black-owned businesses across lenders with different levels of automation is larger in areas with more racial animus. 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 is consistently higher in areas with more racial animus, even after controlling for firm and loan characteristics. (We rule out that racial animus in these specifications is simply proxying for other relevant local characteristics). Similarly, in areas with high racial animus, Black-owned businesses are particularly unlikely to obtain their PPP loans from the smallest traditional lenders. Furthermore, we find that the positive effect of bank automation on the lending rates to Black-owned businesses is larger in locations with higher racial animus. These findings offer support for the conjecture that automation might reduce taste-based racial discrimination in the loan origination process.

Our results so far highlight that process automation is associated with higher rates of lending to Black-owned businesses, both across lender types—where the most automated fintech lenders make the largest share of loans to Black-owned businesses, while the least automated small lenders make the smallest—as well as within lenders that automate their loan origination process over time. We find evidence that this is partly because automated lenders can profitably make smaller loans that are particularly common for minority-owned businesses, and partly because automation reduces the potential for discrimination by humans faced with decisions such as which loan to prioritize in the face of capacity constraints.

However, while fintech firms, large banks, and small banks differ in how much they have automated their loan origination processes—which affects the extent of human biases in prioritization and approval decisions—they also differ on other characteristics that likely contribute to the observed across-lender heterogeneity in lending to Black-owned firms. In the remainder of the paper, we thus explore whether the across-lender patterns can be *fully* explained by such differences, including racial differences in firms' PPP application behaviors or pre-existing banking relationships. (Importantly, none of those differences could plausibly confound our most cleanly identified within-bank analysis of the causal effects of bank automation on lending to Black-owned firms). While we cannot confidently determine how much these other factors contribute to the overall across-bank conditional racial disparities in PPP lending to Black-owned firms, we can conclude that racial disparities in approvals of otherwise similar completed PPP applications at banks (but not at fintechs) contribute meaningfully to the observed patterns.

A first possible alternative explanation for the observed across-lender patterns is that Black-owned firms are more likely to borrow from fintech lenders not because they are more likely to be rejected by conventional lenders, but instead only because they are more likely to *apply* to fintech lenders. Barkley and Schweitzer (2020, 2022) document such racial differences in small business loan application behaviors using data from the Federal Reserve's Small Business Credit Survey. Since the public SBA data only contain information on granted PPP loans (and not applications), we assess this possibility using data on PPP loan applications from the marketplace lending platform Lendio. We observe about 280,000 completed PPP loan applications which Lendio routed quasi-randomly to both conventional banks and fintech lenders, with applicants having no control over where their application was routed.

Among applications routed to fintech lenders, we observe no racial disparities in the chance of getting a PPP loan from that lender. In contrast, among PPP applications routed to conventional lenders, Black-owned firms were 3.9 percentage points (12.3%) less likely to obtain a PPP loan from that lender. Furthermore, Black-owned firms were 5.8 percentage points (15.9%) more likely to get *no PPP loan at all*—through Lendio or otherwise—when their application was routed to a conventional lender. These results are magnified when the application was routed to a small bank. Therefore, the least automated lenders appear the most likely to reject PPP loan applications from Black-owned firms, relative to otherwise similar firms with owners of other races. This finding shows that lower rates of originating completed PPP loan applications from Black-owned firms at banks (but not at fintechs) contributes to the observed across-lender disparities in lending to Black-owned firms. It also highlights important real effects of automation: automation not only affects the identity of the final PPP lender, but also the ability of Black-owned firms to obtain PPP loans at all.

Next, we explore whether the across-bank findings largely reflect conventional lenders preferentially serving their own clients. Such a mechanism could help explain the racial disparity in PPP lending if Black-owned businesses did not bank with active PPP lenders. We test this hypothesis with bank statement data from Ocrolus, a firm that digitizes and analyzes financial documents for financial institutions. These bank statements include information on bank and credit relationships as well as cash flows. Within the matched sample of about 170,000 PPP borrowers—which selects on having a checking account and a prior 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. Although we show that banks did preferentially serve their own customers, this fact is orthogonal to the observed racial disparity, in large parts because there were no large racial differences in the patterns of credit or banking relationships, at least within this sample. Instead, the racial disparity across lenders is driven by the 65% of firms of all races that got their PPP loans from banks other than their checking account bank and therefore had to establish a new banking relationship. Among these firms, Black-owned businesses were much more likely to obtain their PPP loan from a non-relationship fintech lender, and much less likely to obtain it from a non-relationship small bank.

Finally, we test whether differences in firm performance or fraud can explain our results. First, while there was no credit risk from originating the federally guaranteed PPP loans, conventional lenders might still have prioritized firms that appeared to be more profitable future customers. However, the observed racial disparities are unaffected by controls for monthly credit and debit card revenues or bank statement cash flows. This suggests that conditional on our baseline controls, there was no substantial differential performance of Black-owned firms that correlates with the identity of their PPP lender. Second, we assess whether higher rates of fraudulent PPP applications from Black-owned businesses combined with systematically tighter compliance standards at small banks in particular could explain the across-lender patterns, but find evidence that differential fraud rates do not drive the results.

Several contemporaneous papers offer results consistent with ours. Erel and Liebersohn (2020) show that fintech lenders made more PPP loans in areas with higher minority population shares. Fairlie and Fossen (2021) also find that total PPP loan flows to an area were negatively correlated with the minority share of the population. Relative to these papers, we document that even within a given geography, fintech lenders disproportionately lent to Black-owned firms, so bank branch location cannot fully explain the observed patterns. In work complementary to ours, Chernenko and Scharfstein (2021) use rich data on restaurants to study PPP take-up. They show that minority-owned businesses are less likely to get PPP because of the lower take-up of PPP loans from banks, which is only partly offset by greater take-up of PPP loans from fintechs. Our analysis establishes the degree of automation in the lending process as a key factor in explaining variation in PPP lending to minority-owned firms across banks and over time, in part by reducing racial biases; we also rule out differential application behaviors and other factors as alternative explanations.[1]

Our work contributes to an extensive literature studying bias against Black people across a wide variety of settings (Arnold et al., 2018; Bertrand and Mullainathan, 2004; Knowles et al., 2001; Anwar and Fang,

[1]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). We also contribute to a literature exploring how the COVID-19 pandemic and associated policy responses affected small businesses (Alekseev et al., 2020; Bartik et al., 2020a,b; Fairlie, 2020; Kim et al., 2020; Hubbard and Strain, 2020; Faulkender et al., 2020; Granja et al., 2020; Autor et al., 2020; Bartlett and Morse, 2020).

2006; Charles and Guryan, 2008; Price and Wolfers, 2010), including racial disparities in access to financial services (see, for example, the work by Tootell, 1996; Bayer et al., 2018; Bhutta and Hizmo, 2021; Ambrose et al., 2020; Giacoletti et al., 2021; Begley and Purnanandam, 2021; Blattner and Nelson, 2021). Most directly relevant is the work on the role of race in small business lending (Blanchflower et al., 2003; Robb and Robinson, 2018; Fairlie and Robb, 2007; Asiedu et al., 2012; Bellucci et al., 2013; Fairlie et al., 2020).

More broadly, our findings are relevant to the current debate about fintech lenders' role in the financial system (Seru, 2019; Philippon, 2019; Federal Reserve, 2020; Ranson, 2020; Gopal and Schnabl, 2020; Ben-David et al., 2021). Most directly related to this paper is a literature that has explored the role of fintech lenders in extending credit to traditionally underserved minorities (Buchak et al., 2018; Tang, 2019; Fuster et al., 2019; Balyuk et al., 2020; Berg et al., 2020; D'Acunto et al., 2020; Bartlett et al., 2021; Atkins et al., 2021). We contribute by focusing on the role of automation, which enables lenders to profitably make smaller loans and largely eliminates the role of *human* bias. Through this channel, automation at fintech lenders and traditional banks can contribute to lowering racial disparities in credit outcomes.

1 The Paycheck Protection Program: Setting and Data

The Paycheck Protection Program (PPP) was established as part of the Coronavirus Aid, Relief and Economic Security Act ("CARES Act"), passed on March 27, 2020. The PPP provided federally-guaranteed loans to firms that certified their businesses were "substantially affected by COVID-19." To facilitate the speedy disbursal of PPP funds, the federal government outsourced the origination of PPP loans to private lenders. While the SBA approved lenders and individual loans, this 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. In practice, it was largely left up to the private lenders to determine which PPP applications to prioritize, and media reports early in the PPP raised concerns that banks facing capacity constraints 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, 11.8 million loans, administered by 5,467 lenders and totaling over $800 billion, had been approved.

PPP Terms. PPP loans were government-guaranteed and uncollateralized. The loan amount was fixed at 2.5 times the firms' monthly pre-COVID payroll. A PPP loan was forgivable—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 January 9, 2022, 81% of loans and 85% of loan value had already been forgiven. In the event that a loan was not forgiven, repayment would begin six months after the loan had to be used *plus* a 10-month grace period. At that point, loan maturity was two years, and the interest rate was set at 1%. The SBA compensated lenders for originating and servicing PPP loans according to the following upfront fee schedule:

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

As a result of their pre-existing loan infrastructures, conventional lenders were widely reported to face capacity constraints in processing the large volume of PPP applications (e.g., Buchanan, 2020). 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 Federal Reserve's PPP Liquidity Facility to come online, which only occurred several weeks into the program. This facility enabled banks, and later fintechs, to post PPP loans as collateral for new funds to originate loans. Fintechs also participated by partnering with originating charter banks, such as Celtic. In our analysis below, we control for the week of PPP loan approval to ensure that our results are not affected by these time-series patterns of lender participation.

Lender Obligations and Risks. In originating PPP loans and processing forgiveness applications, lenders faced lower compliance burdens than when making conventional loans.[2] 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)."

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 the precise policy early in the program—which is one reason we ensure the results are robust to both excluding or restricting to the first few weeks of PPP loan approvals—legal experts were clear that lenders faced minimal enforcement risk.[3] This benefited smaller banks, which typically have less robust and less automated compliance infrastructure.[4]

[2]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).

[3]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).

[4]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 minimal lender risk in the PPP context is important for our conclusions, let us summarize the lender's risks via a series of questions. First, what happens if the borrower doesn't use the loan as intended? The loan is not forgiven, and the borrower enters a repayment plan. Second, what happens if the 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, unlike for other credit decisions, lenders faced *de minimis* risk in PPP lending.

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 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.

Since our goal is to understand lending behavior in a relatively representative population of both lenders and borrowers, we also drop loans made after February 23, 2021. The Biden Administration made drastic changes to the PPP at this time, which included first prioritizing loans to small firms with less than 20 employees, and then permitting only Community Development Financial Institutions (CDFIs) to use PPP funds. This leaves us with 5.7 million PPP loans for our baseline analysis. However, our results are very similar when we use the full time period and when we include second draw loans.

1.2 Lender Classification

One part of our analysis explores differences in PPP lending to minority-owned businesses across lenders with different degrees of automation. We classify 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 banks;
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;[5]
5. Credit unions: Based on the lender name (i.e., having "credit union" or "CU" at the end of the name);
6. Community Development Financial Institutions (CDFIs) and nonprofits;
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.[6]

[5]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.

[6]Appendix Table A.1 lists all lenders classified as "fintech." In some cases, the originator listed in the table made loans primarily

Table 1 shows how PPP loan origination varied across these lender types for the full sample (Panel A) and the analysis sample with predicted race (Panel B). Focusing on Panel B, traditional banks originated 73% of PPP loans, with non-top-4 banks responsible for 58% of all loans. Fintech lenders originated 17.4% of all PPP loans, while credit unions and MDIs each originated about 4%, and CDFIs 2%. Fintech and other non-bank lenders made substantially smaller loans. The average (median) PPP loan amount for fintech lenders is $31,228 ($15,338) compared to, for example, $87,164 ($20,833) for small banks.

Across-Lender Variation in Automation. The degree of process automation differs widely across these different types of lenders. On one end of the spectrum are fintech firms, which achieve substantial cost savings by fully automating their loan origination processes. But automation also varies substantially among traditional lenders, where it is widely believed to increase in bank size, with one industry observer noting that *"Large banks have avidly adopted robotic process automation…It's tougher for smaller banks to follow suit"* (Crosman, 2020). Indeed, while the largest banks have invested extensive resources in augmenting human loan officers with substantially automated processes,[7] manual processes persist at smaller banks where individual employees have considerable leeway in decision-making. For example, one industry article profiled the PPP strategy of a small SBA-preferred bank in Georgia: *"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).[8]

We confirm these perceptions of differences in the degree of automation across and within conventional lenders using data on bank branch-level IT spending for the years 2017-2019, provided by SWZD.[9] We observe spending data from 106,776 branches of 3,381 unique conventional PPP lenders. Following He et al. (2021), we use software spending to proxy for investment in automation, and construct average annual

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, was founded in 2008, and has received VC funding, so we consider it 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 fintechs 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.

[7]For example, JPMorgan Chase noted that it processed four years worth of small business loan applications in 23 days for the PPP, which it attributed to a *"strategic decision to use a combination of digital plus human capacity"* (Roberts, 2020). Similarly, Sharon Miller, the head of small business at Bank of America explains BofA's success in extending a large number of PPP loans as follows: *"the investments that we've made for digital capabilities, have really helped set us apart from the rest because we were able to quickly get up and running…In 45 days, we processed 18 years' worth of loans"* (Bhattacharyya, 2020). Despite this substantial process automation, and unlike at fintech lenders, humans also remained actively involved in the loan origination process at BofA: *"We're digital first but we still have that human element, the combination of high tech and high touch."*.

[8]As a result the largely manual loan processing, humans with all their potential biases play a larger role in the loan origination process at smaller banks. 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."* Providing a specific example, she continues: *"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."*

[9]These data are sold as market intelligence to technology firms, and used to be known as the Harte Hanks Market Intelligence Computer Intelligence Technology database, and have been used by Forman et al. (2012), Bloom et al. (2014) and He et al. (2021). He et al. (2021) show that the data cover more than 80% of the U.S. commercial banking market.

branch-level software spending between 2017 and 2019.[10] Panel A of Appendix Figure A.1 shows the distribution of branch-level software spending for different bank types (Appendix Table A.7 provides further summary statistics). Median annual spending is over $58,000 for branches of top-4 banks but less than $30,000 for branches of small banks. While there are some challenges with interpreting these data—notably that they measure flow spending over a relatively short time horizon rather than the stock of automation investment—these data confirm that automation is increasing in bank size. This conclusion is also consistent with the longer-term analysis in He et al. (2021), who show that there has been little growth over time in IT spending at small banks, contrasting with substantial growth at large banks.

1.3 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 contain details on owner race for a 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 obtain 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.[11] For non-employer firms, we also use that the "business name" reported in the PPP data usually corresponds to the owner's name. Finally, we obtain 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 involves two steps. First, we follow the methodology in Imai and Khanna (2016) and combine 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 (see Appendix A.1 for details). In the second step, we combine 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 more than 800k PPP loans with self-reported race, a successfully geolocated address, an identified owner name, and information on firm industry and employer status. The model estimates the probability that a borrower belongs to a certain race given first and last name, location, industry, and employer status. For our baseline analysis, we identify the borrower to be of the race with the largest probability across the set of racial groups $\mathcal{R}$.[12]

[10] He et al. (2021) write that *"The specialty of these software products lies in automatically processing information from loan applicants' paper document packets through specialized programming and AI technologies, which would otherwise be done manually by loan officers. By greatly enhancing the efficiency in document assembly, digitization, and information classification, these software improve accuracy and shorten processing speed."* As discussed in He et al. (2021) when a bank's headquarters incurs the expenditure, but the IT is used by the branches, the spending is distributed to the branches rather than appearing only at headquarters.

[11] The owner is identified as the first individual listed as owner or principal under "business contacts" in Secretary of State filings.

[12] The probability distributions for each race as predicted by the algorithm are summarized in Appendix Table A.3 and Appendix Figure A.2. For example, among people predicted to be Black, the mean chance of being Black according to the algorithm is 76%, with a median of 80%. All results in the paper are robust to only considering individuals where this probability is larger than 90%,

In total, we can predict the race of 4.18 million unique PPP borrowers. For the remaining firms, we do not observe the owner name or the geolocation fails. We also exclude about 30,000 loans for which the algorithm predicts the owner race to be "Other." Panel A of Appendix Table A.3 shows that the model correctly predicts the vast majority of the self-reported sample. For example, of those we predict to be Black, 95% self-identify as Black (9.1%/9.6% $\approx$ 0.95). To assess the out-of-sample quality of the prediction, we randomly set aside a "hold-out" sub-sample of borrowers who self-identify their race but whom we exclude from the training of the random forest model. Panel B of Appendix Table A.3 shows that in the hold-out sample, 75% of those business owners that we predict to be Black self-identified as Black (5.7%/7.6% $\approx$ 0.75).

We show below that our main results on the effects of both across-lender and within-lender variation in automation are robust to using the subsample of borrowers for whom the SBA data includes information on self-identified race. However, the signal in our predicted race is likely to be more relevant to our setting because loan officers typically only observe applicants' names and locations, but not their self-identified race. Therefore, they are likely to respond to the race or ethnicity most associated with a given name, rather than to the borrower's actual race or ethnicity. For example, two of the prediction algorithm's "errors" in the holdout sample are individuals whose last names are Huang and Rodriguez, and who self-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 individuals, and our algorithmically assigned race may correspond more closely to the race inferred (and potentially acted upon) 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 "analysis sample." Panel B of Table 1 and Panel A of Appendix Table A.4 show 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 and business type are similar across the full first-draw sample and the analysis sample (Table A.2, Panel A; Appendix Table A.5). For example, the average PPP loan amount is $93,784 in the full sample and $93,666 in the analysis sample. 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).[13]

Other Data. Below we describe other sources of data—including business checking account data from Ocrolus, PPP loan applications from Lendio, credit and debit card transactions from Enigma, and bank automation data from Biz2Credit—used to explore the mechanisms behind the observed racial disparities.

2 Automation and Lending to Minority-Owned Businesses

Lenders can automate many aspects of the loan origination process, allowing them to remove humans from processes such as application intake, information transfer to internal software systems, payroll verification, and fraud checks. Such automation can raise lending to minority-owned firms through several mechanisms:

or when we use this probability directly instead of a race dummy.

[13] The racial composition of our PPP analysis sample is also similar to that of the population of U.S. small business owners. For example, Appendix Table A.6 shows 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.

1. Automated loan processing systems reduce the fixed cost of originating each PPP loan. They also expand the capacity of total loans that can be processed. Through both channels, more automated lenders would be able to serve smaller businesses with demand for lower loan amounts, which are more likely to be minority-owned (see Table 2).
2. Automation generally goes hand-in-hand with an online loan origination process. This allows automated lenders to more easily serve customers in regions with higher minority shares that are traditionally underserved by existing bank branch networks (Wang and Zhang, 2020).
3. Automation reduces the role of human decision-making in the lending process and can thus reduce racial discrimination—whether of the taste-based or statistical variety—in lending.

There are also forces through which process automation may hinder lending to minority-owned firms. For example, if more automated lenders provided less personalized help to borrowers to complete their application materials, and if such help was particularly valuable for minority-owned firms, this would be channel through which more automated lending systems might reduce lending to minority-owned firms. The overall effect of automation on lending to minority-owned firms is thus an empirical question.

In this section, we begin by exploring the empirical relationship between the degree of automation in the loan origination process and rates of lending to minority-owned firms. We find that automation is associated with higher rates of PPP lending to minority-owned firms, both within and across lenders. In the following sections we provide evidence that each of the three factors described above contributes to this pattern.

2.1 Across-Lender Variation

While about 8.6% of PPP loans in our analysis sample went to Black-owned firms, there is wide heterogeneity across lenders. We begin by exploring the relationship between across-lender variation in extending PPP loans to minority-owned business the extent of automation across lenders.

Panel A of Figure 1 shows the share of PPP loans to Black-owned firms by lender type (see also Panel B of Table 1). At the lower end of the distribution, 3.3% of PPP loans originated by small banks went to Black-owned firms. At large banks, Black-owned firms represent 5.3% of originated PPP loans, while top-4 banks made 6.2% of their PPP loans to Black-owned firms. At the top end of the distribution, CDFIs made 10.6% and fintech lenders made 26.5% of their PPP loans to Black-owned firms (CDFIs, unlike fintechs, provide financial services specifically to economically disadvantaged and underserved communities). Overall, fintech lenders were responsible for 53.6% of PPP loans to Black-owned firms in our sample (Panel B of Figure 1, Panel A of Table 2). 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.

We present the corresponding figures for other racial and ethnic groups as well as for gender in Appendix Figures A.4 and A.5. Lending to Black-owned firms exhibits the most striking disparities across lender types, motivating our focus on better understanding the determinants of PPP lending to these firms in particular. Fintechs are somewhat more likely to lend to Asian- and Hispanic-owned firms relative to small- and medium-sized banks. Motivated by evidence that women, like minorities, face challenges in accessing financing and career opportunities (Ewens and Townsend, 2020; Egan et al., 2022; Howell and Nanda, 2022), we also consider gender. While the disparities are smaller, the general patterns are similar: the share of loans to female-owned firms is largest for fintech lenders and smallest for small and medium-sized banks.

In Panel B of Appendix Figure A.1, we group conventional lenders into quintiles of their average branch-level software spending, and show the average share of PPP loans to Black-owned firms in each of these quintiles. Lending to minority-owned firms among conventional lenders is increasing in this measure of the extent of automation. Overall, we consistently find that lenders with larger investments in automating their processes are more likely to extend PPP loans to minority-owned firms.

2.2 Event Study of Bank Automation

While the prior analysis shows a strong correlation between the extent of automation and PPP lending to Black-owned firms, one might naturally be concerned about omitted variables that could be driving the observed relationships: banks and fintech lenders might differ on a range of characteristics other than automation that can affect both the propensity for minority-owned firms to apply as well as the propensity to approve completed loans from minority-owned firms. To identify a causal effect of automation on PPP lending to Black-owned firms, we exploit the adoption of automation during the PPP by a number of small and medium-sized banks. We study how these banks' rates of lending to Black-owned firms changed around the automation event compared to the lending patterns at otherwise similar banks that did not automate.

Data. Our first source of bank-level automation dates is the fintech firm Biz2Credit, which offers a white-label SaaS product called Biz2X that banks could license to outsource and automate their loan processing and underwriting. During the PPP, some banks—motivated by the influx of PPP loan applications—hired firms such as Biz2Credit to automate their lending processes. Once a bank automates using Biz2X, loan application materials are automatically redirected from the bank's website to Biz2Credit. For PPP loans, Biz2Credit then automatically processes documents such as tax filings and proof of business documentation, conducts fraud checks, ensures compliance with PPP eligibility rules, makes a decision, and forwards the required materials back to the bank to originate the loan. Importantly, the "front-end" bank website that the customer faced did not change around automation. Biz2Credit provided us with the launch dates of their service for their clients during the PPP. We also manually searched newspaper articles to identify additional automating banks.[14]

We obtain automation dates for 20 small and medium-sized 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 and medium-sized banks. Table 3 shows summary statistics for the automating banks and the control group of otherwise similar non-automating banks. Among automating banks, about half of their PPP loans occur after automation. Automating banks are somewhat larger than banks in the control group.

The Effect of Automation. Table 3 shows that, on average, automating banks' share of loans to Black-owned businesses increased after automation, from 4.4% to 12% (there are also smaller increases in the share of loans to Hispanic-owned and Asian-owned firms, and corresponding declines in the share of PPP loans to White-owned firms). However, these average increases could reflect a broader increase in loans to Black-

[14]These banks often automated via other fintech service providers, including Customers Bancorp, Numerated, and Fountainhead. For some of these manually identified automation events, we only have a rough date of automation, potentially creating some noise in our estimation. We find similar results when restricting our analysis only to banks that automated through Biz2Credit.

owned businesses over time among all banks, or a specific secular trend in lending to Black-owned businesses among automating banks. To isolate the effect of automation separately from such potential time trends, we estimate the following dynamic differences-in-differences specification using all PPP loans originated by small and medium-sized banks in our analysis sample:

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

$\mathbb{1}(\text{BlackOwned}_{ibt})$ indicates whether loan i originated by bank b in month t went to a Black-owned business. A_b corresponds to the month in which bank b automates, and $\mathbb{1}(t - A_b = k)$ is an indicator for being k months away from that automation date. The coefficients are relative to the omitted period, $k = -1$, which represents the month prior to automation. The model also includes fixed effects for bank and origination period.

Panel A of Figure 2 plots the β_k coefficients from the dynamic differences-in-differences model in Equation 1. We do not report more than three months of pre-automation data because the set of automation dates mean that we rarely observe PPP loans four months before an automation event (automation dates are mostly in late Spring 2020, and then after a period in which the PPP was inactive, in late Fall 2020). We observe no differential pre-trends in the rates of lending to Black-owned businesses among automating banks prior to automation. In contrast, following automation, automating banks have a persistent increase in the rate of lending to Black-owned businesses relative to other, non-automating banks. This finding is consistent with a causal effect of automation on banks' rates of extending PPP loans to Black-owned firms. It is also consistent with the across-lender patterns of lending to Black-owned firms presented above.

We conduct two robustness checks. First, we find similar results in the smaller and potentially selected sample of individuals that self-report race (Appendix Figure A.8). Second, we estimate Equation 1 at the weekly level for a banks that originate loans for six weeks on both sides of the automation date. The results 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 (Appendix Figure A.9).

In the following sections, we explore the importance of the various mechanisms described above in driving the observed relationship between automation and lending to Black-owned firms. We will also rule out a variety of other factors, such as racial differences in loan application behavior or banking relationships, as the only determinants of the observed across-lender differences in lending to minority-owned firms.

3 Mechanisms: The Role of Loan Size and Firm Characteristics

As discussed above, a key mechanism through which automation can increase lending to Black-owned firms is through reducing the fixed cost of lending and increasing processing capacity. Both of these factors would allow lenders to originate more PPP loans with smaller loan amounts—precisely the types of loans that the relatively smaller Black-owned firms are disproportionately eligible for. In addition, more automated lenders (and fintech firms in particular) generally acquire and originate their loans online, allowing them to serve borrowers independent of their locations. In contrast, traditional banks disproportionately acquire customers through their branch networks, which have less presence in minority neighborhoods.

To assess whether firm characteristics such as firm size and location can explain the striking unconditional variation across lenders in serving Black-owned businesses, we use the regression framework in Equation 2:

$$\mathbb{1}(\text{LenderType}_i) = \beta \mathbb{1}(\text{BlackOwned}_i) + \mathbf{X}_i \delta + \varepsilon_i. \tag{2}$$

The dependent variable, $LenderType_i$, is an indicator for whether PPP borrower i gets their loan from a certain type of lender. The key explanatory variable is an indicator for whether a firm is Black-owned, defined as in the previous section. For example, when $LenderType_i = Fintech_i$, the coefficient β measures the higher propensity (in percentage points) of Black-owned firms to get their PPP loan from a fintech lender, relative to all other racial and ethnic groups. $\mathbf{X}_i$ represents a vector of control variables.

Lending to Black-Owned Firms by Fintech Lenders. Panel A of Table 4 shows results from regression 2, with $LenderType_i = Fintech_i$. Column 1 shows that, consistent with Section 2.1, Black-owned businesses have a 39.7 percentage point higher unconditional probability of obtaining their PPP loan through a fintech lender, a large difference given that only 17.4% of all firms obtained their PPP loans through fintechs.

We first consider whether the timing of PPP applications explains some of the unconditional racial disparity in lender identity. As shown in Appendix Figure A.10, the share of PPP loans to Black-owned firms and the share of PPP loans made by fintechs both increased over time (see also Appendix Table A.8). While this relationship might be causal—with Black-owned firms successfully obtaining PPP loans only after fintech lenders entered the program—it could alternatively reflect coincidental timing, with Black-owned firms only applying for PPP loans later in the PPP. Since we cannot separate these two explanations, we focus on understanding disparities among loans originated at the same time. Those disparities are unlikely to be confounded by timing factors unrelated to automation, and present a lower bound on the total disparities that are determined by lender characteristics. Column 2 of Table 4 shows that even after controlling for week-of-loan-approval fixed effects, Black-owned businesses are 26 percentage points more likely to obtain their PPP loan from a fintech lender.

We next consider the effect of loan size. 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 2). In the PPP program, lenders were compensated for originating loans with a fixed fraction of the loan amount. If automation reduces origination costs or increases loan processing capacity, fintechs could profitably make more PPP loans to the small loan segments disproportionately comprised of Black-owned firms. Consistent with such a story, Table 1 shows that the average PPP loan size for fintech-originated loans is about one-third of the average loan size in the overall PPP. In column 3 of Table 4, Panel A, we add fixed effects for each percentile of the loan size distribution. Controlling for loan amount explains some of the disparity, consistent with the ability to serve smaller loans partially contributing to fintech lenders serving more Black-owned businesses. However, Black-owned firms remain 23.2 percentage points more likely to receive fintech loans even after controlling for loan size.

Next, we consider the role of firm location. Fintech lenders may have been more accessible to businesses in areas underserved by bank branch networks because fintech PPP applications were generally completed entirely online. Therefore, in column 4 of Table 4, Panel A, we add zip code effects to the specification from column 2. Fintech lenders' ability to reach firms across all geographies indeed appears to account for some of their higher share of loans to Black-owned firms: controlling for firm location reduces the disproportionate probability of Black-owned firms borrowing from a fintech lender from 26 percentage points to 20.7 percentage points (see also Erel and Liebersohn, 2020).[15]

Finally, we explore the role of industry. Small businesses have notoriously heterogeneous business models across industries, making them difficult for banks to assess (Mills, 2018). In addition, banks may prefer working with small firms from certain sectors, for example those with more formalized accounting practices. In contrast, fintechs have developed automated technologies to lend to traditionally underserved industries. For example, they have invested in computer-reading and automatically processing diverse documents, including handwritten payroll slips, creating an advantage in sectors with less formal accounting systems, which have higher shares of Black-owned firms.[16] We include industry fixed effects in column 5 of Table 4, Panel A to control for such industry-specific differences.[17] Even within the same industry, Black-owned firms are 21.9 percentage points more likely to obtain their PPP loans from fintech lenders.

Jointly controlling for all firm characteristics explains just over half of the unconditional difference in the probability of obtaining a PPP loan from a fintech lender between Black-owned and non-Black-owned firms obtaining their PPP loans at the same time (column 7 vs. column 2 of Table 4, Panel A). This finding suggests that fintech lenders are indeed more likely to lend to Black-owned firms in part by making smaller loans, by operating in otherwise underserved locations, and by lending to types of businesses less likely to be served by conventional lenders. However, even after we include this rich set of controls, Black-owned businesses remain 12.1 percentage points more likely to obtain their PPP loan from a fintech lender than otherwise identical businesses owned by individuals of a different race or ethnicity.

Lending to Black-Owned Firms Across Conventional Lenders. As discussed above, conventional lenders differ substantially in how they process loan applications. Large banks have more automated and standardized lending processes than smaller banks, though even large banks' processes are not nearly as automated as those of fintech lenders. Section 2.1 highlighted that the variation in the degree of automation across conventional lenders aligns closely with their unconditional rates of lending to Black-owned firms.

In Panel B of Table 4, we explore the extent to which this unconditional variation in lending to Black-owned firms across conventional lenders can be explained by observable differences across firms. We replace $LenderType_i$ in Equation 2 with an indicator for obtaining the PPP loan from a top-4 bank (columns 1 and 2), a large bank (columns 3 and 4), or a small/medium bank (columns 5 and 6). Unconditionally, Black-owned firms are less likely to get their loans from all of these types of banks, consistent with the findings described above. After including the full set of controls, this relationship is close to zero for the top-4 banks. The majority of the 12.1 percentage point fintech disparity in column 7 of Panel A of Table 4 is accounted for by lower rates of PPP lending to Black-owned firms by small and medium-sized banks, exactly those banks with the lowest degree of automation in the loan origination process.[18] These small and medium-sized banks

[15] In Appendix Table A.9, 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.

[16] Based on conversations with executives at Kabbage and the New England Regional SBA Office senior leadership.

[17] 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 2 Panel A shows that industry distribution differ by owner race. For instance, businesses in the "Personal and Laundry Services" sector are more likely to be Black-owned than firms in the "Specialty Trade Contractors" sector.

[18] Figure 3 visualizes the conditional across-lender patterns by comparing all types of lending institutions simultaneously. 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 controls. The fraction of fintechs' loans to Black-owned firms was over five

were instead disproportionately likely to lend to White-owned firms (see Appendix Table A.10).

We also use the previously described data on branch-level software spending at conventional lenders to see whether this proxy for automation is associated with more PPP lending to Black-owned firms. Specifically, we match each firm obtaining a PPP loan from a conventional lender to the software spending at her lender's local branches.[19] In Panel C of Table 4, we present results from Equation 2 using the log of branch-level software spending between 2017-2019 as the dependent variable. The results line up with the across-lender-type analysis. Unconditionally, Black-owned firms obtain their PPP loans from branches with about 7.3% higher spending on software in 2017-2019. Conditioning on firm location and firm characteristics reduces but does not eliminate this disparity. Importantly, even within the same bank, Black-owned businesses are more likely to get their PPP loans from a branch with higher software spending than from a similarly sized branch of the same bank with lower software spending.

The Causal Effect of Automation at Small and Medium-Sized Banks. We next explore whether smaller loans are part of the reason why automation caused banks to increase their loan shares to Black-owned firms during the PPP period (see Section 2.2). Such a mechanism would be consistent with evidence that automation substantially increased banks' lending capacities during the PPP, allowing them to process more of the lower-amount (and thus lower-fee) loan applications from Black-owned firms.[20] To explore how much of the treatment effect of automation can be explained by compositional changes in loan characteristics on non-race dimensions, we use a standard differences-in-differences model:

$$\mathbb{1}(\text{BlackOwned}_{i,b,t}) = \alpha_b + \alpha_t + \beta \mathbb{1}(\text{PostAuto}_{b,t}) + \mathbf{X}_i \delta + \varepsilon_{ibt}. \tag{3}$$

The dependent variable is an indicator for whether PPP loan i made by bank b in week t is to a Black-owned firm. $\mathbb{1}(\text{PostAuto}_{b,t})$ is an indicator for bank b having automated—i.e., having started service with Biz2Credit or another white-label fintech—as of week t. α_b is a bank fixed effect, and controls for any baseline differences in lending to Black-owned firms; α_t is a fixed effect for the week of loan approval, removing any general time trends in the share of loans by small banks to Black-owned firms. $\mathbf{X}_i$ represents firm and loan controls that we add sequentially. The coefficient of interest β captures the effect of automation.

We report results from estimating Equation 3 in the sample of all PPP loans originated by small and medium-sized banks in Panel A of Table 5. The baseline differences-in-differences model controlling only

percentage points higher than the fraction for other lender types. MDIs made a disproportionate share of their loans to Asian-owned firms. 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 do this, we first construct branch-level software spending at the zipcode level for each bank, exclude the bank headquarters site. We then match PPP borrowers to software spending at the bank-zipcode level. For example, a PPP borrower in zipcode 10012 who got a PPP loan from Citibank would be matched to the average software spending for Citibank branches in 10012. When the bank has multiple branches but none in the borrower's zipcode, we use the average of all branches in the borrower's county. When there is no county match, we use the bank's nationwide average, though all results are robust to only using PPP loans that we can match at the zip code level. Overall, we can match about 2.9 million PPP borrowers to bank branch software spending.

[20] 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]."* 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."*

for bank and time fixed effects is presented in column 1. The coefficient implies that the share of loans to Black-owned firms increased by six percentage points after automation, relative to a pre-automation share of 4.4%. In column 2, we add the same set of controls as in Table 4, Panel A, column 7. The magnitude of the β-coefficient declines by about one-third, but remains at 4.3 percentage points. At 98% of the pre-automation share of Black-owned borrowers (4.4%), this is economically large.[21]

Panel B of Figure 2 shows the coefficients from the dynamic differences-in-differences regression 1 after adding the full vector of controls (as in Table 5, Panel A, column 2). As before, prior to automation, the trends in lending to Black-owned businesses among automating banks are the same as those at non-automating banks. Following the automation, banks increase their rates of lending to Black-owned businesses, though the magnitude of the increase is somewhat smaller than in the unconditional specification shown in Panel A.

Appendix B presents robustness tests of these across-lender main findings. For example, we show that the results are similar in the smaller and potentially selected sample of individuals that self-reported race. Other tests document persistent effects across time periods within the PPP as well as when separately considering, for example, employer vs. non-employer firms.

4 Mechanisms: The Role of Discrimination

So far, we have documented that the automation of lending processes is associated with a higher probability of lending to Black-owned firms. This is true both in the cross-section of lenders, where fintech lenders and (to a somewhat lesser extent) the largest banks with more automated lending processes tend to grant more PPP loans to Black-owned businesses. It is also true within lenders, where we find increased lending to Black-owned firms after banks automate their loan origination processes. Controlling for loan size, firm location, and other firm characteristics reduces the racial disparities associated with automation by between one-third and two-thirds. But even when comparing loans to otherwise similar firms in a setting with no credit risk, more automated lenders are substantially more likely to lend to Black-owned firms.

Beyond the mechanisms explored above, automation could also reduce racial disparities by removing human biases from any decision-making during the manual review and processing of PPP applications. Loan officers may become aware of applicant race through channels such as the applicant's name, which we have shown to be highly predictive of race,[22] or visually through manual review of applicants' drivers licenses, which were required in color for all PPP applicants. If preference-based discrimination contributed to the observed higher probability of otherwise similar Black-owned firms obtaining a PPP loan from automated lenders, the disparity should be larger in regions with higher racial animus. We next explore this hypothesis by studying the interaction of the degree of automation with geographic variation in racial animus.

Racial Animus Data. We collect six geographic measures of anti-Black racial animus. The first measure is the share of an area's Google searches that contain racially charged words from Stephens-Davidowitz (2013). The second measure follows Bursztyn et al. (2021) and is based on how favorably White respondents rate

[21] In columns 3-5 of Table 5 Panel A, we consider how lending to non-Black-owned firms was affected. Following automation, we see a small increase in the rate of lending to Hispanic- and Asian-owned firms. All of the increase in lending to Black-owned firms following automation comes at the expense of White-owned firms.

[22] 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).

Black Americans as a group in the Nationscape survey (Tausanovitch and Vavreck, 2020). The third measure comes from the Implicit Association Test (IAT), which assesses implicit bias against Black individuals. The fourth measure is from a survey question that explicitly asks individuals who just took the IAT for their feelings towards Black Americans (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 dissimilarity index captures differences in the distributions of White and Black residents across city tracts. The isolation index estimates the probability of a Black resident sharing the same city tract with another Black resident.

Appendix A.3 describes the six measures of racial animus in more detail, and examines their geographic variation as well as the degree to which they are correlated with one another. Importantly, Appendix Figure A.14 shows that the places where racial animus is high differ substantially across our measures, indicating that they offer somewhat independent signals of animus.

Across-Lender Racial Disparities by Racial Animus. Table 6 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 each panel, column 1 includes the same right-hand side variables as in column 7 of Table 4, Panel A. In columns 2-7, we additionally interact the indicator for being Black-owned 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 racial animus measure is standardized to have a mean of zero and a standard deviation of one, so that the coefficients can be interpreted as the effect, in percentage points, of a one standard deviation increase in the racial animus measure on the probability of Black-owned firms obtaining their PPP loan from a specific lender type.

In Panel A of Table 6, 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 firm ownership. The coefficient magnitudes vary from 0.4 to 2.9 percentage points across the various measures. 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 firm obtains its 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, we find robust evidence that in areas with higher racial animus, Black-owned firms are particularly likely to obtain their PPP loans from fintech lenders.

Prior analyses showed that Black-owned firms' substitution toward fintechs came primarily from smaller banks. If racial discrimination at small banks explains some of our findings, the pattern in Panel A should reverse when we consider the probability of obtaining PPP loans from smaller banks. Panel B finds precisely this relationship. For example, the coefficient using the implicit bias (IAT) measure implies that a one-standard-deviation higher racial animus score is associated with a 4.2% decrease in the chance that Black-owned firms get their PPP loans from a non-top-4 bank. Consistent with prior findings, Panel C shows that the propensity of top-4 banks to lend to Black-owned firms does not vary with the degree of racial animus.

In Appendix Table A.17, we show that our measures of racial animus in these specifications do not just proxy for local levels of education and income among Black people, and their possible effects on the probability of Black-owned firms to obtain PPP loans from different lender types. Specifically, we interact the indicator for Black-owned with county-level measures of the percent of Black people with at least a Bachelor's degree and the median Black household income, both from the Census 2019 ACS. If anything, the interaction between local racial animus and Black-owned is even stronger with these additional interactions.

The Effect of Bank Automation by Racial Animus. In Panel B of Table 5, we examine whether the effect of automation on the share of loans to Black-owned businesses is larger in areas with higher racial animus. There are positive and significant interactions for four of the six measures, with the remaining two being positive but marginally not significant at conventional levels. In terms of magnitude, the interaction coefficient for the implicit bias test implies that automation increased the share of PPP lending to Black-owned firms by about 20% *more* in areas with one standard deviation higher racial animus. Appendix Table A.12 Panel B repeats the analysis on the subset of loans with self-reported race and ethnicity and finds similar results. This finding provides additional evidence that one of the mechanisms through which automation increases those loans is by reducing the effect of preference-based discrimination.

5 Mechanisms: Loan Applications and Rejections

Our analysis so far has studied racial difference in PPP lender identity among firms that ultimately received PPP loans. Our interpretation of the observed racial disparities involves less automated conventional lenders—and in particular smaller banks—having a higher tendency to not process or to reject the PPP applications of Black-owned firms, both because Black-owned firms are generally smaller and thus only eligible for smaller and less profitable PPP loans and because of racial discrimination.[23]

We next use PPP application data to address possible concerns that our across-bank results might instead only reflect Black-owned firms applying more frequently to fintech lenders (as documented in other settings by Barkley and Schweitzer, 2020, 2022), perhaps because of a particular fintech affinity in this population or because they anticipate less discrimination. While such differences in application behavior would not confound our within-lender analysis, we also show that differential application behavior cannot fully explain our across-bank findings (though our data do not allow us to rule that they contribute to the disparity).[24]

5.1 Lendio Loan Application Data

We obtain data on PPP applications through November 2020 to the marketplace platform Lendio. Firms could submit PPP applications through the Lendio website, which were then forwarded to one or two of around 300 partner lenders that include both fintech firms and conventional banks.

Our conversations with Lendio executives, including CEO Brock Blake, indicate that the routing of applications to lenders was random conditional on loan size, geography, and capacity criteria set by the lender partners. Lenders then decided whether to approve the application, complete the SBA approval (duplicate check) process, and finally fund successful applicants. As the application through Lendio

[23] Investigative reporting (Morel et al., 2021; Zhou, 2020) and survey data (Small Business Majority survey) suggest widespread rejections of PPP loan applications. For example, in a survey of around 10,000 employer firms, the Federal Reserve found that approval rates varied between about 75% and 90% depending on the lender type (Fed Small Business Survey Data). One of the largest lenders was reported to reject more than 90% of applications (Flitter and Cowley, 2020).

[24] To the extent that Black-owned firms are less likely to apply to conventional lenders because they correctly anticipated disparate treatment, the main thrust of our findings remains unchanged. Indeed, substitution away from lenders that discriminate may partially explain demand for fintech products more generally.

included all necessary components and was screened for completeness, the lender typically did not have further interactions with the borrower. Importantly, applicants did not know which bank their applications would be forwarded to when applying through Lendio, and they had no control over the application routing. Therefore, these data permit us to largely hold fixed the application behavior of firms.

We observe 278,404 applications that Lendio forwarded to at least one lender. The average application was routed to 1.5 lenders, composed of 0.9 fintechs and 0.6 conventional lenders (Appendix Table A.18). Among the firms whose PPP applications were forwarded by Lendio to at least one lender, just over 60% ultimately got a PPP loan, while the remaining 40% did not end up receiving any PPP loan at all. Among firms that got a PPP loan, about 40% received the loan from one of the lenders to which its application was forwarded by Lendio, while the rest got the loan from a different lender.

Statistics about the Lendio sample and its demographic breakdown are summarized in Panel C of Appendix Table A.4. The loan amount is the actual PPP loan amount except for the "No PPP Loan" category, in which case it is the amount sought as reported by Lendio. The average loan amount for borrowers sent only to fintechs is less than half the amount for borrowers sent only to conventional lenders, likely due to fintechs specifying lower target loan amounts at Lendio because of lower fixed costs per loan.

5.2 Analysis of Lendio Loan Applications

In Table 7, we analyze PPP loan outcomes for applicants through the Lendio platform. We consider two outcomes: (i) whether the firm ultimately gets its PPP loan from a lender to which Lendio sent the firm's application, and (ii) whether the firm fails to obtain any PPP loan.

When pooling across all PPP applications in our sample, we find that Black-owned applicants are less likely to get a PPP loan from one of the lenders to which their application was forwarded by Lendio, even after controlling for a wide range of firm characteristics (column 1). The regression specification includes fixed effects for the identity of the lenders the application was sent to. Our findings thus imply that, conditional on an application to a given lender, Black-owned firms are less likely to obtain a PPP loan from that lender. Column 2 shows that, in addition, Black-owned firms are also less likely to get any PPP loan at all compared to otherwise similar firms with non-Black ownership forwarded to the same lender.

In columns 3 and 4 of Table 7, we restrict the sample to PPP applications that were sent only to fintech lenders (recall that, conditional on loan characteristics, it is random which lenders an application gets forwarded to). Among PPP applications that are routed to fintechs lenders, Black-owned firms face *no* differential chance of getting a PPP loan from that lender (column 3). This is consistent with Black-owned firms facing no disparate treatment at fintech lenders. Black-owned firms routed to fintech lenders did face a slightly higher chance of getting no PPP loan at all (column 4). The difference between columns 3 and 4 is driven by racial disparities in PPP outcomes among the sample of firms that were unable to obtain their eventual PPP loan through Lendio. While column 3 shows that, conditional on controls, this sample is not selected on race, some of these firms would subsequently apply to conventional lenders where they would face the same disparities described in Section 4.

In columns 5 and 6 of Table 7, we restrict the sample to PPP applications that were forwarded only to conventional lenders. Among those applications, Black-owned firms are 3.9 percentage points less likely to get a PPP loan from a Lendio lender and 5.8 percentage points less likely to get any PPP loan at all. Note that the differences between columns 3 and 5 do not reflect fintechs being more permissive in general; the average rate of originating Lendio loans is, in fact, somewhat lower at fintechs than at conventional lenders. Instead, the result in column 6 represents a real effect from higher rates of rejection for Black-owned firms at conventional lenders. It indicates that Black-owned firms are 5.8 percentage points, or 15.9% of the mean, more likely to obtain no PPP loan at all when their application is forwarded only to conventional lenders. In columns 7 and 8, we further restrict the sample to loans that Lendio forwarded to small banks, those banks with the least automated processing sytems on average. Consistent with our prior findings, racial disparities in obtaining PPP loans are largest among applications forwarded to this group of lenders.

In sum, racial differences in the propensity to apply to different lenders cannot fully explain the main across-lender disparities (in addition to not explaining our within-lender findings). Instead, disparities in lender decisions to process or approve completed PPP applications at least partly explains why Black-owned firms are more likely to receive fintech loans, and less likely to receive small bank loans. This behavior has important real effects. Black-owned firms whose application is quasi-randomly assigned to be processed by conventional lenders are less likely to get any PPP loan at all, in addition to being less likely to get a PPP loan from that lender. There are no comparable racial disparities among firms whose applications are assigned to be processed by fintech lenders. This finding highlights that automation does not only affect *which lender* Black-owned firms get their PPP loan from, but also whether they obtain a PPP loan *at all*. Whatever the determinants of the racial disparities identified in this paper, they have important real effects.

6 Mechanisms: Bank and Credit Relationships

There is substantial evidence that many banks tended to first serve their own clients' PPP loan applications, for example because processing these applications was lower cost or because PPP loans might enable clients to repay pre-existing loans to the bank (Granja et al., 2020; Flitter and Cowley, 2020). If banks prioritized their own clients in distributing PPP loans, and if Black-owned businesses were less likely to 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 (though again, it should not confound the within-lender analysis). We directly assess this hypothesis using a sample of PPP borrowers matched to bank statement data.

6.1 Bank Statement Data

We work with data from Ocrolus on firms' bank statements through July 2021. Ocrolus digitizes documents for fintech companies, including business checking account statements used in the underwriting process, and thus has a large repository of such 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.

Panel C of Table 1 shows that the bank statement sample and the full analysis sample are broadly similar on dimensions such as loan amount. Firms with bank statements are somewhat more likely to be minority-owned. The main dimension of selection is that firms with matched bank statements have higher rates of fintech PPP loans—36.3%, compared to 17.4% in the analysis sample. This reflects that Ocrolus processes loan applications for many fintech clients, thus selecting on firms with fintech affinity or experience.

We define a firm's checking account bank as the bank that issued the statement. In addition, text descriptions of transactions in the bank statements permit us to identify credit relationships. Specifically, we use the existence of a transaction to or from a lender to indicate a credit relationship—loan, credit line, or credit card—with this lender. Since these relationships include business credit cards, they are much broader than other sources of data, such as UCC filings for secured debt. Among all borrowers, 14.2% had a credit relationship with a fintech firm, while 80% had a credit relationship with a traditional bank (Table 2, Panel B). The share of firms with access to external financing in the Ocrolus sample is relatively high because Ocrolus obtains 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). We also use the bank statement data to calculate monthly cash inflows and outflows as a measure of firm financial performance. Panel B of Table 2 shows that the mean net monthly cash inflow across all firms is \$9,016, while it is \$6,332 among Black-owned businesses.

6.2 Banking Relationship Analysis

Consistent with media reports and previous literature, we find that conventional banks' PPP clients were also often their business checking account clients. Panel C of Table 1 shows that 27.6% of PPP borrowers had a checking account at their PPP lender. About two-thirds of all PPP loans originated by the top-4 banks went to checking account clients of those banks. For other large banks, this number is 49.1%, and for medium and small banks, it is 38.7% and 22.8%, respectively. For fintech lenders, which do not usually offer checking accounts, this number was essentially zero.

Although conventional lenders served their own clients at higher rates, we show in Table 8 that this fact does not explain the higher rate of fintech PPP loans for Black-owned firms. First, in column 1, we estimate the fully controlled model from Table 4, Panel A, column 7, in the bank statement-matched sample. In this sample, Black-owned firms are 5.5 percentage points more likely to obtain their PPP loan from a fintech lender. In column 2, 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 and other firms with a checking account at JPMorgan Chase. The inclusion of these fixed effects has essentially no effect on the differential probability of Black-owned firms to obtain their PPP loans through fintech lenders.

In Panel B of Table 8, we find that, as in the full sample, Black-owned firms in the Ocrolus matched sample have no differential chance of a top-4 PPP loan (column 1), but are substantially less likely to get a small bank PPP loan (column 5). As with fintech loans in Panel A, these relationships do not attenuate much with the inclusion of checking account bank fixed effects. Therefore, the racial disparity in this dataset does not reflect Black-owned firms holding their checking accounts at banks that were less active as PPP lenders.

We next assess whether there are racial differences in the propensity of a firm to obtain its PPP loan from its checking account bank. In Table 9, we split the sample of checking account holders by the identity of the checking account bank. Among firms with checking accounts at top-4 banks, Black-owned firms have the same chance as other firms of getting their PPP loan from their checking account bank (column 1 of Table 9, Panel A). Black-owned businesses are slightly less likely than other groups to obtain their PPP loans from their checking account banks if they bank with non-top 4 banks (column 1 of Table 9, Panels B and C).[25]

In column 2 of Table 9, we show that Black-owned firms' differential chance of getting a fintech loan is similarly large regardless of where they have their checking account, and exists even for borrowers with checking accounts at top-4 banks. The subsequent columns show that this reflects variation in PPP lender types among firms that do *not* get their PPP loan from their checking account bank.

These results highlight two channels that contribute to the higher rate of fintech loans among Black-owned firms. 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 whose PPP lenders were not their checking account banks, 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. Consistent with the earlier findings, the disparity in this sample is largest among new clients at small banks—those banks with the least automated application systems—with no evidence of substanatial disparate treatment at top-4 banks.

We next explore whether prior credit relationships explain PPP lending patterns. In column 3 of Table 8, Panel A, 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. 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: Black-owned firms 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 (Table 8, Panel A, column 3).

In Section 7, we showed that differential propensities of Black-owned firms to apply to fintech lenders are unlikely to explain the observed racial disparities in PPP lender identity. We further explore a specific such mechansims, which suggests that one reason Black-owned firms may have been more likely to apply to fintechs is that they may have been more tech-savvy or have had higher fintech affinity. To test this hypothesis, 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 (Panel D of Table 9). This finding implies that the main results are unlikely to be driven by higher fintech affinity among Black-owned firms.

[25] Many newspaper articles offer examples of Black-owned businesses failing to obtain PPP loans through their checking account banks. For example, the Associated Press interviewed Lisa Marsh, th Black owner of MsPsGFree, a Chicago-based 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).

7 Other Possible Explanations: Performance and Fraud

The previous results suggest that automation explains an important part of the variation across lender types in PPP lending to Black-owned firms. In Appendix B, we consider two final mechanisms that might contribute towards explaining the observed cross-bank effects (though they could not explain the within-bank effects): contemporaneous firm performance and fraud. Here, we briefly summarize the tests and their results.

First, one might be concerned that lenders treated Black-owned firms differently because those firms experienced particularly negative pandemic shocks. To assess the validity of this concern, we obtain data from Enigma, which observes at at least 60% of all U.S. debit and credit card transactions, on overall monthly credit card revenues. We can match more than 800,000 PPP borrowers to the Enigma data. Although this sample is composed of firms that are, on average, larger and more sophisticated, Black-owned firms are still 17% more likely to get a fintech PPP loan. Adding controls for card revenue has no effect on this disparity. Therefore, racial differences in the real-time performance of firms does not explain the results.

A final possibility is that the across-lender variation in lending to Black-owned firms could result from differential statistical discrimination by lenders based on their differential fraud rates. In particular, 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 racial disparities in lender identity. Appendix B presents a variety of evidence that this hypothesis is unlikely to explain our findings.

8 Conclusion and Discussion

The original legislation authorizing the PPP included an explicit mandate to prioritize socioeconomically disadvantaged businesses. Yet, in practice, many conventional banks did not serve Black-owned firms in proportion to their share in the PPP borrower population. Instead, it was fintech lenders that made a disproportionate share of loans to Black-owned firms, 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 firms. 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 argue that varying degrees of automation across lender types help to explain these patterns. First, we find that racial differences in loan shares across lenders align with differences in the rates of automation, with the most automated lenders (fintechs) making the largest share of loans to Black-owned firms, and the least automated lenders (small banks) making the smallest share. Second, we show that after conventional lenders automated their lending processes, their rates of lending to Black-owned businesses increased substantially. Borrower characteristics—including location, loan amount, loan approval date, industry, and business form—can explain some but not all of the unconditional disparity between fintechs and other lenders. Some of these characteristics are related to the channels through which automated lending can increase credit access for Black-owned firms. For example, automation enabled fintechs to make smaller loans. Since loan size in the PPP was tied to payroll and Black-owned firms tend to be smaller, this benefited Black-owned firms.

However, even with a rich array of controls, Black-owned businesses remain about 12 percentage points more likely than other firms to get their PPP loan from a fintech lender. Moreover, we show that differential pre-existing bank relationships, firm application behavior, real-time revenue, fintech affinity, and fraud rates cannot fully explain this gap. Instead, we find suggestive evidence that preference-based discrimination helps to explain lower rates of lending to Black-owned businesses among smaller conventional lenders. Since many of the variables we condition on partially reflect historical patterns of discrimination (e.g., location controls to capture the distribution of bank branch networks), the substantial differences in our controlled models represent a lower bound on the overall effect of discrimination on small business lending patterns.

One important conclusion from our results relates to the important ongoing conversation about the equity effects of new technologies in the provision of financial services. While there are legitimate concerns that the use of algorithms may lead to discriminatory effects, for example because these algorithms are trained on biased data, our results suggest that there may be substantial equity benefits from automation. Specifically, by eliminating the manual review conducted by biased humans, automation could reduce the incidence of taste-based discrimination. A promising area for future research is whether there are similar equity benefits from other financial activities such as securitization that increase the weight placed on hard information in lending decisions, thus reducing the scope for taste-based discrimination.

The PPP setting has many advantages to help understand the effects of automation on racial disparities in access to credit, most notably by removing the need for banks to evaluate credit risk. However, while we believe that the broad findings in this work are likely to extrapolate to other settings, there are reasons to expect the overall magnitude of the effect of automation on racial disparities to not translate directly. For example, in particular during the early COVID period, the economic cost to conventional lenders from any taste-based racial discrimination was relatively small: PPP loan applications dramatically exceeded banks' processing capacities, and any decision to not process a loan application from a Black-owned firm could generally be substituted with the processing of an equally profitable application from a White-owned firm. One would expect that in other settings with less binding capacity constraints, economic forces might push more strongly against substantial taste-based discrimination, leading to lower observed racial disparities. On the other hand, during the COVID period, even small banks dramatically reduced in-person service and typically accepted PPP applications online (see Appendix Figures A.6 and A.7). In our setting, most of the effects of differential automation therefore occur only after the application arrives at the financial institution, in processes such as payroll verification. As a result, one might expect that racial disparities caused by automation might be larger in a normal lending market in which small banks are doing more of their business in person (Arnold et al., 2018; Knowles et al., 2001; Price and Wolfers, 2010). Better understanding the magnitudes of racial disparities across other lending markets is thus an important avenue for follow-on research.

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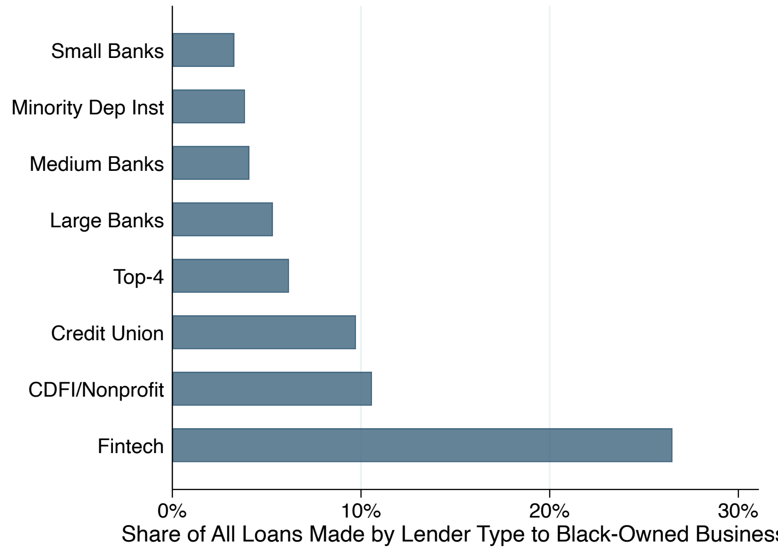
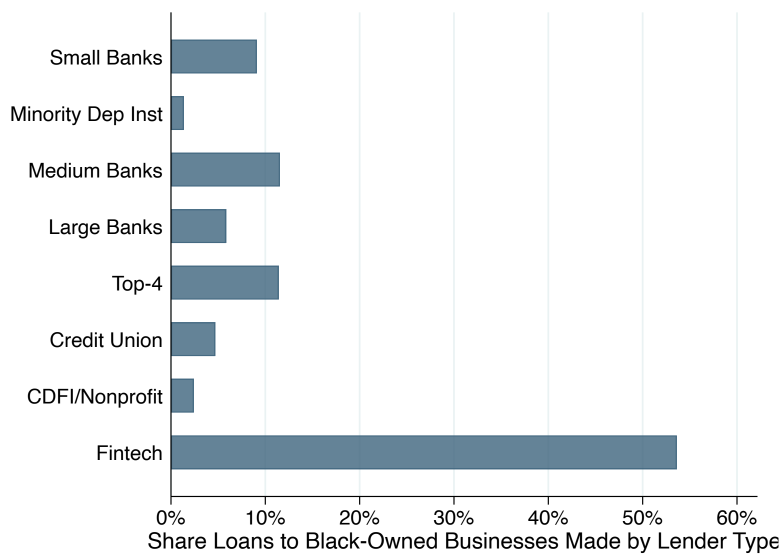
Figure 1: **Black-Owned Business PPP Lending by Lender Type**

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



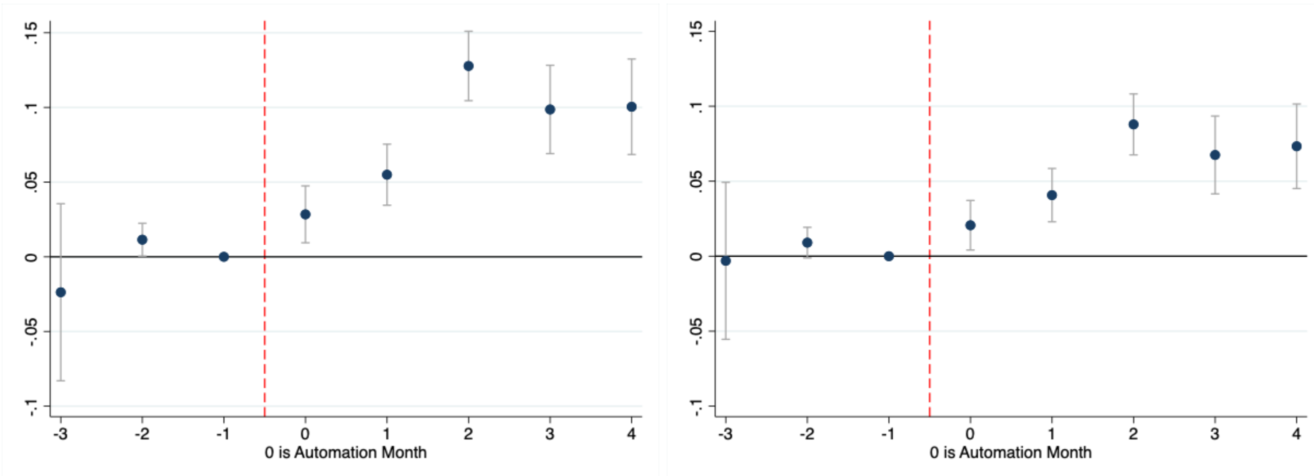
(B) Share of Lender Type among PPP Loans to Black-Owned Businesses



Note: Panel A shows, for each lender type, the share of PPP loans that went to Black-owned businesses (P(Black-owned|Originating Lender Type)). Panel B shows the share of all PPP loans to Black-owned businesses made by each lender type (P(Originating Lender Type|Black-owned)).

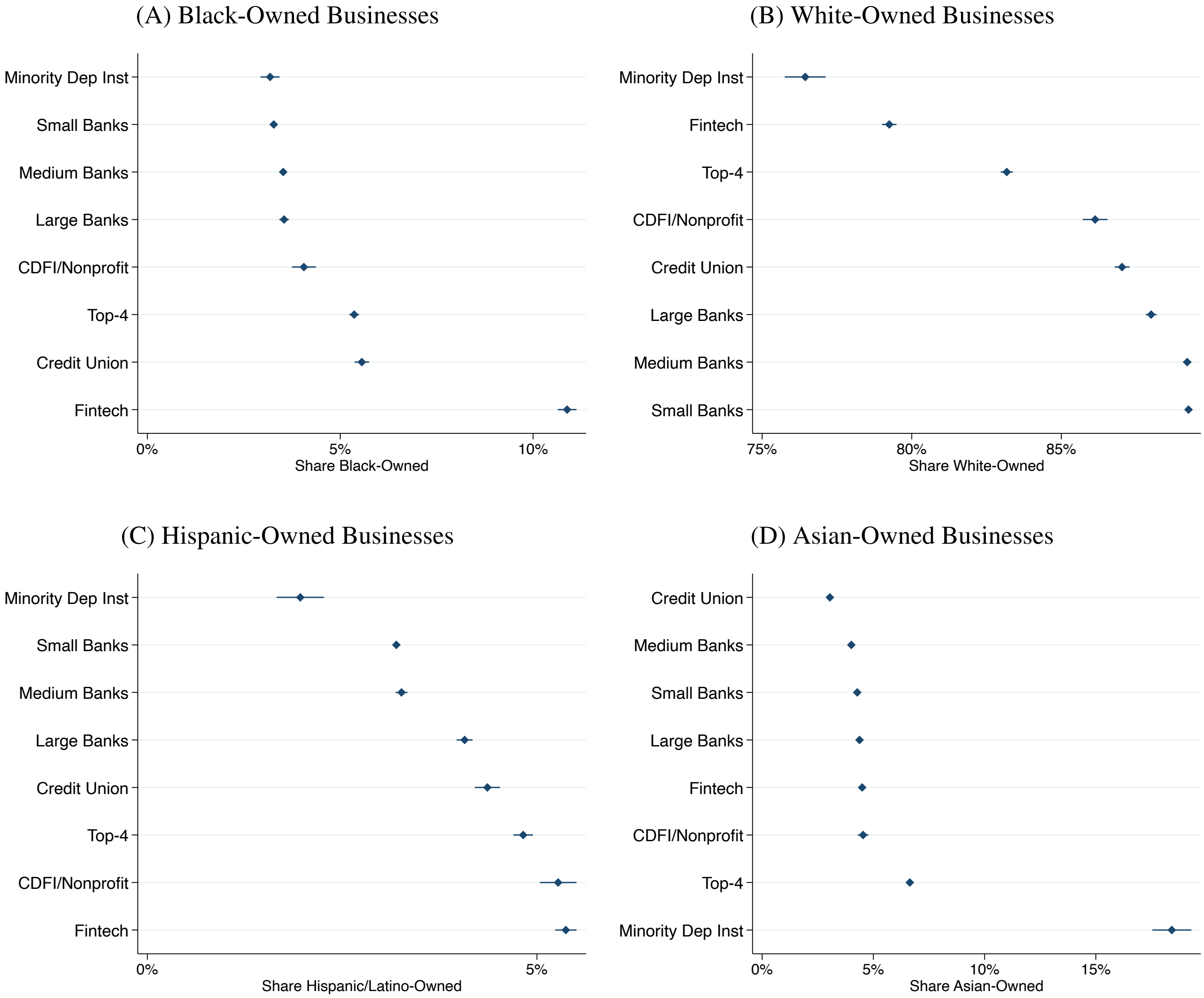
Figure 2: **Share of Loans to Black-Owned Businesses Before and After Small Bank Automation**

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



Note: This figure reports dynamic differences-in-differences estimates at the monthly level (see Equation 1). Period 0 following the dashed vertical line corresponds 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 5, Panel A, column 2. We do not include more than three months before automation because the automation dates (in late Spring 202 and in late Fall 2020 following a large gap in the PPP program) mean that we observe essentially no loans made four months prior to automation dates. Standard errors are clustered by zip code. The grey bars represent 95% confidence intervals.

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



Note: This figure shows shares of PPP loans made to Black-owned businesses by originating lender type. Each graph presents β-coefficients from variants of the following regression: $\text{Black-owned}_i = \beta \text{Lender Type}_i + \gamma \mathbf{X_i} + \epsilon_\mathbf{i}$, 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. The mean of the omitted category, small banks, is added back to each panel. In each panel, we change the dependent variable to be an indicator for whether a borrower is a Black-owned (Panel A), White-owned (Panel B), Hispanic-owned (Panel C), or Asian-owned (Panel D) business, multiplied by 100 to facilitate the interpretation of coefficients.

Table 1: Summary Statistics by Lender Type

Panel A: All PPP Loans

	Number Lenders	Number Loans	Total Amt ($ bn)	PPP Loan Amount ($)			
				Mean	P10	P50	P90
All	4,889	11,768,450	798.7	67,867	4,199	20,678	124,500
Top-4	4	1,258,063	94.6	75,165	5,181	21,578	140,241
Large Banks	17	898,175	108.8	121,127	6,000	28,133	230,895
Medium Banks	377	2,139,089	271.3	126,807	6,080	30,405	266,000
Small Banks	3,196	2,385,728	179.0	75,024	4,130	20,832	151,100
Credit Union	946	378,673	15.7	41,479	3,602	15,882	82,422
CDFI/Nonprofit	187	1,516,834	34.4	22,711	4,400	20,000	20,833
Minority Dep Inst	133	424,976	29.3	68,924	3,823	20,053	131,015
Fintech	29	2,766,912	65.6	23,726	3,083	17,208	29,166

Panel B: Analysis Sample

	Number Lenders	Number Loans	Total Amt ($ bn)	PPP Loan Amount ($)				Share Black Borr	Share White Borr
				Mean	P10	P50	P90		
All	4,845	4,183,623	391.9	93,666	4,462	20,833	176,900	8.6%	75.0%
Top-4	4	663,471	53.0	79,901	5,000	21,744	145,497	6.2%	67.0%
Large Banks	17	393,884	57.7	146,505	6,250	32,100	279,297	5.3%	81.4%
Medium Banks	377	1,018,578	145.2	142,532	6,200	33,600	295,300	4.1%	84.0%
Small Banks	3,186	997,879	87.0	87,164	4,510	20,833	174,500	3.3%	89.3%
Credit Union	926	173,368	7.9	45,412	3,550	16,000	89,567	9.7%	78.1%
CDFI/Nonprofit	175	82,276	5.9	71,564	3,904	20,800	145,833	10.6%	74.4%
Minority Dep Inst	132	127,283	12.5	98,406	4,800	22,100	190,022	3.9%	56.9%
Fintech	28	726,884	22.7	31,228	2,853	15,338	54,465	26.5%	49.2%

Panel C: Bank and Credit Relationships Sample (Ocrolus)

	Number Loans	Mean Loan Amount	SME Has Checking Acct with PPP Lender	Credit With Any:		Monthly Net Cash Inflow ($)		Share Black Borr	Share White Borr
				Fintech	Non-Fintech	Mean	P50		
All	168,360	80,897	27.6%	14.2%	80.0%	9,016	1,332	15.3%	63.5%
Top-4	29,709	72,738	67.6%	15.6%	87.3%	11,939	2,773	8.4%	63.6%
Large Banks	15,179	104,023	49.1%	14.7%	82.3%	12,226	2,491	8.1%	74.6%
Medium Banks	28,459	133,265	38.7%	14.5%	75.5%	9,347	1,477	5.9%	78.2%
Small Banks	21,284	118,637	22.8%	14.4%	75.4%	7,706	1,251	6.1%	80.1%
Credit Union	5,644	56,194	34.7%	13.0%	72.0%	6,794	825	14.2%	69.5%
CDFI/Nonprofit	3,046	66,732	8.5%	13.6%	79.1%	8,141	1,178	17.8%	61.4%
Minority Dep Inst	3,984	114,058	21.4%	14.2%	75.5%	5,263	1,122	5.4%	47.0%
Fintech	61,055	42,379	0.0%	13.3%	80.7%	7,592	932	28.7%	48.6%

Note: This table reports summary statistics about PPP loans by originating lender type. Panel A describes all PPP loans, while Panel B focuses on our analysis sample, which is composed of first draw PPP loans between April 3, 2020 and February 23, 2021 for which we can predict the borrower's race. 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 borrowers in the analysis sample that we can match to bank statement data from Ocrolus. The column ”SME has Checking Account with PPP Lender” captures whether 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. Appendix Table A.2 repeats Panels B and C for the subset without predicted race.

Table 2: 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					
Top-4	15.9%	27.4%	11.4%	24.1%	14.2%
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%
Other	11.9%	8.3%	26.2%	15.8%	10.3%
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

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

Note: This table reports summary statistics by race/ethnicity. Panel A contains loan and firm characteristics for the analysis sample. Panel B summarizes information from the bank statement-matched data.

Table 3: Summary Statistics on Automation during PPP among Small and Medium-Sized Banks

	Automating Banks N = 20			Non-Automating Banks N = 3,870		
	Mean	P50	SD	Mean	P50	SD
Number of Loans	3,748	1,250	6,062	504	186	1,627
Assets (Million $)	8,673	1,235	15,078	1,242	262	4,786
Loan Amount ($)	131,297	129,011	61,355	77,826	58,980	74,199
Share Loans After Automation	29.9%	17.6%	31.3%			
Asian-Owned Share Before Automation	5.4%	5.1%	3.5%	3.5%	1.8%	5.7%
Asian-Owned Share After Automation	7.3%	5.4%	10.4%	3.5%	1.8%	5.7%
Black-Owned Share Before Automation	4.4%	3.3%	5.0%	2.7%	1.0%	4.8%
Black-Owned Share After Automation	12.0%	11.4%	11.6%	2.7%	1.0%	4.8%
Hispanic-Owned Share Before Automation	5.3%	3.6%	6.8%	3.0%	1.1%	7.3%
Hispanic-Owned Share After Automation	6.4%	5.5%	5.9%	3.0%	1.1%	7.3%
White-Owned Share Before Automation	85.0%	87.7%	13.4%	90.9%	94.3%	11.3%
White-Owned Share After Automation	74.4%	72.6%	21.5%	90.9%	94.3%	11.3%

Note: This table contains summary statistics of the banks used in the automation analysis. Columns present unweighted summary statistics across the sample of automating and non-automating banks. For non-automating banks, the rows "Before Automation" and "After Automation" both show full sample statistics.

Table 4: Business Owner Race and PPP Lender Type

Panel A: Fintech PPP Loan

Dependent Variable:	𝟙(Fintech)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	0.397***	0.260***	0.232***	0.207***	0.219***	0.224***	0.121***
	(0.005)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Approval Week FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	No	No	Yes	No	No	No	Yes
Zip Code FE	No	No	No	Yes	No	No	Yes
Industry FE	No	No	No	No	Yes	No	Yes
Business Type FE	No	No	No	No	No	Yes	Yes
Employer Status FE	No	No	No	No	No	Yes	Yes
Dep Var Mean	0.174	0.174	0.174	0.174	0.174	0.174	0.174
R^2	0.086	0.227	0.240	0.276	0.265	0.272	0.356
Observations	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(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)
Approval Week FE	No	Yes	No	Yes	No	Yes
Loan Amount FE	No	Yes	No	Yes	No	Yes
Zip Code 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: Branch Software Spending and PPP Loans to Black-owned Businesses

Dependent Variable:	Log(Branch Software Spending)					
	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(Black-owned)	0.073***	0.033***	0.027***	0.026***	0.015***	0.008***
	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Approval Week FE	No	Yes	Yes	Yes	Yes	Yes
Borrower County FE	No	Yes	Yes	Yes	No	No
Loan Amount FE	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Business Type FE	No	Yes	Yes	Yes	Yes	Yes
Employer Status FE	No	Yes	Yes	Yes	Yes	Yes
Branch Size FE	No	No	Yes	Yes	Yes	Yes
Bank Size FE	No	No	No	Yes	No	Yes
Bank FE	No	No	No	No	Yes	No
Borrower Zip FE	No	No	No	No	No	Yes
Dep Var Mean	10.803	10.803	10.803	10.803	10.803	10.803
Observations	2,890,666	2,890,666	2,890,666	2,890,666	2,890,666	2,890,666

Note: This table reports estimates of Equation 2. The dependent variable in Panel A is an indicator for whether the originating lender is a fintech firm. Panel B repeats the specifications in columns 1 and 7 of Panel A, using as dependent variables indicators for whether the originating lender is a top-4 bank (columns 1–2), a large bank (columns 3–4), and a small/medium-sized bank (columns 5–6). Panel C is estimated on the sample of PPP loans matched to the bank branch-level software spending data. The dependent variable, the log of "Bank Branch Software Spend", is a measure of automation for the bank branches of the PPP lender within the PPP borrower's zipcode (or county, if there is no zipcode match). Control variables generally 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 seven indicators for the firm's business type. Employer status is an indicator for whether the firm has at least one employee. Additional controls in Panel C are indicators for each percentile of lender assets ("Bank Size") and branch-level revenue ("Branch Size"). Standard errors are clustered by borrower zip code. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Effect of Automation during PPP on Lending to Black-Owned Small Businesses

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

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
Business Type FE	No	Yes	Yes	Yes	Yes
Zip Code FE	No	Yes	Yes	Yes	Yes
Industry 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: Bank Automation on Loan Share by Race and Ethnicity and Racial Animus

Dependent variable:	$\mathbb{1}$(Black-Owned)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(After Automation)	0.041***	0.042***	0.045***	0.042***	0.037***	0.041***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\mathbb{1}$(After Automation) $\times$ Racial Animus	0.009***	0.008***	0.004*	0.005	0.025***	0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Racial Animus Measure	IAT (Implicit)	IAT (Explicit)	Stephens-Davidowitz	Nationscape	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 3, estimated on the sample of PPP loans extended by small and medium banks. Columns 1-2 of Panel A show the effect of automation on the probability that a loan is extended to a Black-owned business. 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 measures of local racial animus (see Table 6), using 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 Table 4. Standard errors are clustered by zipcode. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Black Business Ownership and Lender Identity: The Effect of Racial Animus

Panel A: Fintech PPP Loans as Dependent Variable

Dependent variable:				𝟙(Fintech)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	0.121***	0.120***	0.121***	0.124***	0.121***	0.107***	0.117***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
𝟙(Black-Owned) $\times$ Racial Animus		0.013***	0.011***	0.004**	0.014***	0.029***	0.016***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dep Var Mean	0.174	0.174	0.174	0.174	0.174	0.174	0.174

Panel B: Non-Top-4 Bank PPP Loan as Dependent Variable

Dependent variable:				𝟙(Non-Top-4 Bank)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	-0.106***	-0.103***	-0.105***	-0.107***	-0.105***	-0.093***	-0.103***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
𝟙(Black-Owned) $\times$ Racial Animus		-0.024***	-0.017***	-0.013***	-0.013***	-0.029***	-0.012***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dep Var Mean	0.576	0.576	0.576	0.576	0.576	0.576	0.576

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

Dependent variable:				𝟙(Top-4)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	-0.008***	-0.009***	-0.008***	-0.009***	-0.008***	-0.009***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
𝟙(Black-Owned) $\times$ Racial Animus		0.008***	0.004***	0.010***	-0.001	0.004***	-0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Racial Animus Measure		IAT (Implicit)	IAT (Explicit)	Stephens-Davidowitz	Nationscape	Segregation (Isolation)	Segregation (Dissimilarity)
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code 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

Note: This table reports estimates of a modified Equation 2, 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 non-top-4 bank PPP loan, and in Panel C, it is an indicator for a top-4 bank PPP loan. In each panel, column 1 repeats the specification in Table 4, Panel A, column 7. The racial animus measures are as follows: columns 2-3 use the implicit and explicit score from the Implicit Association Test (IAT) aggregated to the county level; column 4 uses the number of racially charged searches in a designated media market (DMA); column 5 uses responses to the question on favorability toward Black people in the Nationscape survey aggregated to the congressional district 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 Table 4. Standard errors are clustered by zipcode. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Lending to Black-Owned Firms Conditional on Applications

Sent to Lenders:	Any		Only Fintech		Only Conventional		Only Small Banks	
Dependent Variable:	𝟙(PPP Loan from Lendio Lender)	𝟙(No PPP Loan)	𝟙(PPP Loan from Lendio Lender)	𝟙(No PPP Loan)	𝟙(PPP Loan from Lendio Lender)	𝟙(No PPP Loan)	𝟙(PPP Loan from Lendio Lender)	𝟙(No PPP Loan)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Black-owned)	-0.011***	0.021***	-0.000	0.006**	-0.039***	0.058***	-0.056***	0.068***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.005)	(0.005)	(0.010)	(0.009)
Application Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code 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
Sent Lenders FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep Var Mean	0.250	0.396	0.239	0.399	0.316	0.364	0.382	0.375
Observations	278,404	278,404	153,434	153,434	83,328	83,328	36,276	36,276

Note: This table reports estimates of a modified version of Equation 2 within the sample of PPP loan application to Lendio. Columns 1–2 include the whole sample, columns 3–4 restrict to the sub-sample of applications that Lendio quasi-randomly forwarded only to fintech lenders, columns 5–6 restrict to the subsample of loans that were forwarded only to conventional lenders, and columns 7-8 restrict to the subsample of loans that were forwarded only to small banks. In each sample, we consider two dependent variables: an indicator for whether the application eventually resulted in a PPP loan from one of the lenders that Lendio forwarded the application to (columns 1, 3, 5, and 7), and an indicator variable for whether the loan applicant received no PPP loan at all (either through a Lendio lender, or an alternative lender). We include fixed effects for each combination of lenders that the application was routed to. Other controls are as described in Table 4, with the exception that we include application week fixed effect instead of origination week fixed effect. Standard errors are clustered by zipcode. ***,**,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Black Business Ownership and PPP Lender Type with Bank and Credit Relationship Controls

Panel A: Fintech PPP Loan

Dependent variable:	$\mathbb{1}$(Fintech)			
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Black-Owned)	0.055***	0.055***	0.056***	0.055***
	(0.004)	(0.004)	(0.004)	(0.004)
$\mathbb{1}$(Credit from Fintech)			0.075***	0.078***
			(0.003)	(0.003)
$\mathbb{1}$(Credit from Conv.)			-0.012***	-0.011***
			(0.003)	(0.003)
Approval Week FE	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes
Zip Code 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:	$\mathbb{1}$(Top-4 Bank)		$\mathbb{1}$(Large Bank)		$\mathbb{1}$(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Black-Owned)	0.005	-0.000	-0.017***	-0.019***	-0.047***	-0.036***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)
$\mathbb{1}$(Credit from Fintech)		-0.025***		-0.011***		-0.034***
		(0.003)		(0.002)		(0.003)
$\mathbb{1}$(Credit from Conv.)		0.001		0.005**		-0.002
		(0.002)		(0.002)		(0.003)
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
Months Since Statement FE	No	Yes	No	Yes	No	Yes
Checking Acct Bank FE	No	Yes	No	Yes	No	Yes
Monthly Cash Inflow FE	No	Yes	No	Yes	No	Yes
Monthly Net Cash Inflow FE	No	Yes	No	Yes	No	Yes
Bank Statement Sample	Latest	Latest	Latest	Latest	Latest	Latest
Dep Var Mean	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

Note: This table reports estimates of a modified Equation 2, 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), or a small/medium-sized bank (columns 5–6). 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 9: Black Business Ownership and PPP Lender Type by Checking Account Bank Type

Dep Var:	𝟙(Lender is 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
Approval Week FE	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes	Yes
Zip Code 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	Yes	Yes	Yes	Yes	Yes
Checking Acct Bank 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 2, 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 relationships 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 Table 8. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

(For Online Publication)

Internet Appendix for "Lender Automation and Racial Disparities in Credit Access"*

A Supplemental Details on Data Sources and Construction

A.1 Race Prediction Algorithm

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.

A.2 Card Revenue Data

To assess whether the real-time financial performance of small businesses helps explain our results, we 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 Appendix A.4 and in Panel B of Appendix Table A.18. 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-owned firms, $43,422 for Asian-owned firms, and $58,355 for White-owned firms.

A.3 Racial Animus Measures

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

*Howell, Sabrina, Theresa Kuchler, David Snitkof, Johannes Stroebel, and Jun Wong, Internet Appendix to "Lender Automation and Racial Disparities in Credit Access," Journal of Finance. Please note: Wiley is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article."

A.3.1 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

$$\text{Racially Charged Search Rate}_j = \frac{\left[\frac{\text{Google searches including the word “Word(s)”}}{\text{Total Google searches}}\right]_j}{\left[\frac{\text{Google Searches including the word “Word(s)”}}{\text{Total Google searches}}\right]_{\max}}. \tag{1}$$

Figure A.14 Panel A shows the geographical distribution of racially charged searches by DMA, and Figure A.15 Panel A shows the distribution of racially charged searches by DMA.

A.3.2 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.14 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.15, Panel B shows the distribution of individual responses to the question by White respondents.

A.3.3 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.14 Panel C shows the geographical distribution of average IAT scores by county. We omit counties with fewer than 50 respondents. Figure A.15 Panel C shows the distribution of the IAT score at the respondent level.

A.3.4 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.15 Panel D and A.14 Panel D show the response distribution and geographical distribution of the explicit score, respectively. We omit counties with fewer than 50 respondents.

A.3.5 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):

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

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.15 Panel E shows the distribution of the dissimilarity index. Figure A.14 Panel E maps MSA-level residential segregation across the U.S.

A.3.6 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):

$$I_T = \sum_{i=1}^{N} \Big(\frac{b_i}{B_T} \times \frac{b_i}{b_i + w_i} \Big) \tag{3}$$

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.15 Panel F shows the distribution of the isolation index. Figure A.14 Panel F maps the geography of isolation.

B Further Analyses

B.1 Robustness of main results

In this section, we show that our central findings are robust to (i) variation in how we predict owner race; (ii) the sample of firms; and (iii) the exact specification of the firm-level controls.

Race Prediction. We begin by exploring the robustness of our results to our approach to predicting owner race. In our first set of tests, we show that we find similar across-lender results in the smaller and potentially selected sample of individuals that self-reported race (Appendix Table A.11). We show that the within-lender causal effects of automation are also robust to using this sample of firms with self-identified owner race (Appendix Table A.12, Panel A and Appendix Figure A.8, Panel B).

Second, we explore whether, among individuals that our algorithm predicts to be Black, the strength of the race signal correlates with variation in PPP lender type (Appendix Table A.13). The racial disparity in the probability of obtaining a PPP loan from a fintech lender increases monotonically with the strength of the race signal provided by name and location, pointing to a potentially important role for the degree of "Blackness" as suggested by the audit literature (Bertrand and Mullainathan, 2004), and providing additional confidence in the signal produced by our algorithm.

Sample composition. We next explore whether our results are sensitive to the exact composition of the sample. A first question is whether our results are driven by a particular time period. Therefore, we estimate Equation 2 separately for loans approved in each of the four key phases of the PPP program to show that, in each round, fintech lenders made a larger share of their loans to Black-owned businesses compared to traditional lenders (Appendix Table A.14, Appendix Figure A.11).

Another concern is that, since Black-owned firms tend to be non-employers, our results could be specific to the population of small businesses that are sole proprietorships or self-employed. However, we find that the racial disparity in PPP lender identity persists among the sample of employer firms, and—although the magnitudes are somewhat lower in absolute terms—they are higher relative to the mean rate of obtaining PPP loans through fintech lenders (Appendix Table A.15).

Firm Controls. In Appendix Table A.16, we vary the granularity of our fixed effects to address potential concerns that residual within-bin variation could be confounding our results. First, we use 1,000 bins of loan size rather than 100, and find similar results (columns 1 and 6). Second, we replace zip code fixed effects with census tract fixed effects to rule out possible concerns about within-zip code clustering of minority populations in areas with lower branch density (columns 2 and 7). Third, we show that the results do not reflect more narrow industries or certain industries being more likely to be Black-owned in particular locations by verifying that the findings are robust to including 6-digit NAICS industries (columns 3 and 8) or industry-by-zip interacted fixed effects (columns 4 and 9).

B.2 Mechanism: Firm Financial Health

In this appendix, we explore whether differential financial performance of minority-owned firms during the COVID-19 period can explain the racial disparities in PPP lending that remain after controlling for other firm and loan characteristics. In particular, while PPP lenders were not responsible for any PPP loan losses—and firm creditworthiness should thus have been irrelevant to the one-shot decision of making a PPP loan—lenders may still have been more likely to lend to firms in better financial positions. Such behavior could be driven by those firms representing more attractive future customers, or by stickiness in the behavior of loan officers who are used to screening for creditworthiness.

Panel B of Table 2 shows that gross and net inflows at Black-owned businesses are, at the median, less than half of their values than for the other racial groups, consistent with minority-owned businesses being generally smaller and thus less attractive PPP customers. To assess whether differences in revenue affect our results after conditioning on firm size, we add granular controls for a firm's gross and net cash inflows from the most recent bank statement as observed in the Ocrolus data in column 4 of Table 8, Panel A. Black-owned firms 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.[1]

Many of the data points in the Ocrolus data come from prior to February 2020. We additionally would like to explore data on firm performance at the time of the PPP application to assess whether lenders treated Black-owned firms differently because those firms experienced particularly negative pandemic shocks. To do this, we obtained data from Enigma, which observes at at least 60% of all U.S. debit and credit card transactions, on overall monthly credit card revenues (see Appendix A.2 for details on these data). We can match more than 800,000 PPP borrowers to the Enigma data; these firms are, on average, larger than the firms in our baseline analysis sample. In column 1 of Appendix Table A.20, we first re-estimate the main model in this sample to establish a baseline. In this sample, and conditional on controls, 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. 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 contemporaneous credit card revenue has no effect on these racial disparities. This pattern continues to hold when we measure revenue only in the approval month (Appendix Table A.21).

Note the above analysis conditions on observing revenue near the time of the PPP loan application. One remaining concern may thus be that minority-owned firms are doing especially poorly in a way that drops them from this sample—for example, because they have no card revenue in the approval month—and that different lenders' differential treatment of such firms explains part of our findings. To rule out such effects, in Panel B of Appendix Table A.20, we restrict the sample to firms that appear especially harmed by the COVID-19 economic crisis, i.e., 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, and find broadly similar results as in Panel A.

In sum, while the Enigma sample generally includes larger and more consumer-oriented firms—firms among which Black-owned businesses appear to be at less of a disadvantage on average—we find no evidence that differences in real-time revenue among this sample help explain the main findings of differential propensities across lenders to extend PPP loans to minority-owned firms.

B.3 Mechanism: Differential Fraud Rates

We also explore whether the across-lender variation in PPP lending to Black-owned firms could result from a combination of racial differences in fraud rates and across-lender differences in compliance standards. (Note that, as with other possible alternative explanations, such a mechanism could not explain our findings on the within-lender changes in lending to Black-owned firms following the automation of lending processes).

Specifically, if Black-owned firms were substantially more likely to submit fraudulent PPP applications and fintech firms had lower compliance standards (in particular relative to small banks) that reduced their ability to detect these fraudulent applications, this channel could contribute to the observed racial disparities in lender identity.[2] However, several reasons suggest that such a mechanism does not explain our results.

Racial Differences in PPP Fraud Rates. We first explore if there is evidence for more substantial PPP fraud among Black-owned businesses, a necessary condition for this alternative story to explain our results.

[1] We repeat Table 8 with indicators for whether a business is Asian-, Hispanic-, and White-owned in Appendix Table A.19. We continue to find similar results. For example, these regressions show that even 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.

[2] Note that in order to explain the very substantial racial differences in PPP lending across lender types, a very large share of eventually approved PPP applications by Black-owned firms would need to have been fraudulent.

To do this, we use unsealed PPP fraud cases prosecuted by the U.S. Department of Justice as of November 15, 2021.[3] We link the companies named in the affidavits to borrowers in the PPP loan sample. We identify 268 matched cases, and observe race predictions for the owners of 191 implicated firms. Appendix Table A.22 shows the share of these allegedly fraudulent PPP loans originated by different lenders. Consistent with Griffin et al. (2021), we find that fintechs originated 46% of allegedly fraudulent PPP loans, a large share relative to fintech's overall share of PPP loans. However, importantly for our purposes, the share of firms with allegedly fraudulent PPP loans that have Black ownership is 8.4%, almost exactly the Black-owned share of the overall PPP loan sample (8.6%, from Table 1, Panel B). These results highlight that while fraudulent loans were more likely to be originated by fintech firms (perhaps because of lower compliance standards at fintechs), Black-owned firms were no more likely to be implicated in fraud.

We also explore if there are racial differences in small business lending fraud more generally. To assess this, we gather county-level data for 2020 on Suspicious Activity Reports (SARs) from the Financial Crimes Enforcement Network (FinCEN), a U.S. government body. We also use data on small business lending by county in 2020 from Community Reinvestment Act disclosure filings. This permits us to calculate a proxy for the county-level small business lending fraud rate as the number of SARs divided by the number of small business loans. In Panel A of Appendix Figure A.12, we correlate the county-level SAR-based fraud rate with the county share of PPP loans to Black-owned firms. There is no evidence of disproportionate small business lending fraud in locations with more Black-owned firms. In Panel B we also show that fraud rates are no higher in counties where a larger share of PPP loans to Black-owned firms was granted by fintech firms. Overall, there is no evidence of higher fraud rates among loans to Black-owned firms, either during the PPP program or more generally.

Reconciliation with Griffin et al. (2021). Griffin et al. (2021) identify a set of PPP loans with suspicious features, and explore how the share of these suspicious PPP loans varies by lender. The authors highlight that fintech firms had the highest average suspicious loan index, which could be indicative as evidence of those lenders having lower compliance standards. Is it possible that this difference, combined with large racial differences in the propensity to submit fraudulent PPP applications (despite the evidence to the contrary above), can explain the across-lender variation in PPP lending to different racial groups? The authors have generously shared their suspicious loan index data for each lender to help us assess this question.

Appendix Figure A.13 shows that there is indeed a strong positive relationship between the Griffin suspicious loan index and the share of PPP loans to Black-owned borrowers; this relationship is similar across lenders within each lender type. While these patterns might be *prima facie* evidence for a mechanism whereby a larger "suspicious loan index" as a proxy for lower compliance standards causes higher approvals of fraudulent PPP loan applications from Black-owned firms, we believe that the reverse mechanism is a much more plausible explanation of the observed patterns: more loans to smaller and thus more Black-owned firms among fintech lenders—for example, due to more extensive process automation—leads Griffin et al. (2021) to classify more loans as suspicious.

To see this, it is important to realize that Griffin et al. (2021) flag a loan as suspicious if any of the following four indicators are satisfied: (1) the firm does not have a state business registration; (2) there are at least three businesses with PPP loans under the same address; (3) there is a high implied compensation per job reported; or (4) the number of jobs implied by the EIDL advance grant exceeds the number of jobs implied by the PPP loan. While each of these indicators might well be indicative of a higher probability of PPP loan fraud, each is also more likely to be triggered by non-fraudulent loans to Black-owned firms.

For example, regarding criterion (1), note that non-employer firms and sole proprietorships need not (and often do not) register with state governments.[4] Since only 21% of Black-owned PPP borrowers were

[3] We gather cases from the DOJ website and the law firm Arnold & Porter's website.

[4] One business guide explains that "A sole proprietorship is a one-person business that, unlike corporations and limited liability companies (LLCs), doesn't have to register with the state in order to exist."

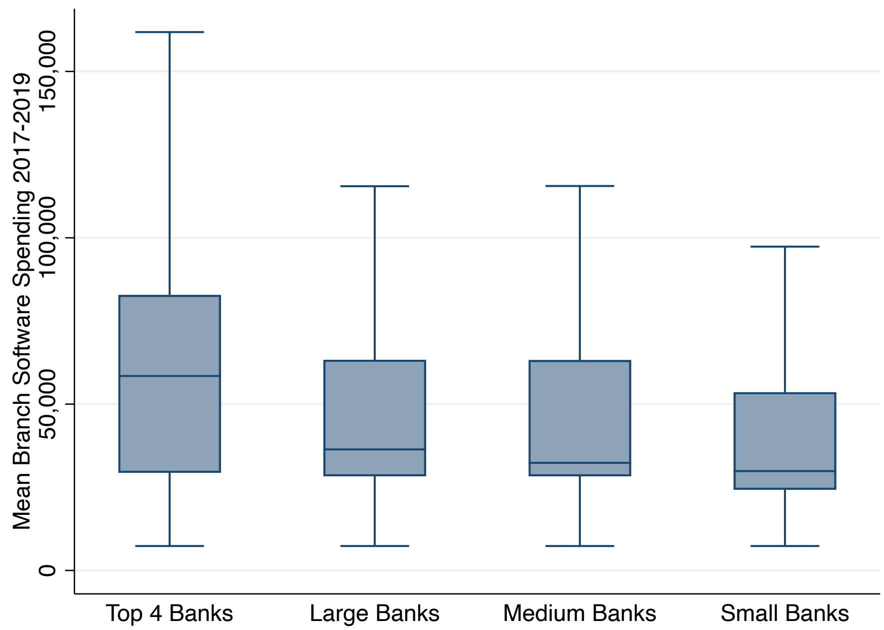
employer firms (Table 2), compared to about 68% of non-Black-owned borrowers, the majority of Black-owned PPP borrowers would not have been required to register their business. All PPP loans to such firms, including non-fraudulent ones, thus have a high chance of being flagged as "suspicious" by Griffin et al. (2021). There are similar reasons to expect that legitimate PPP loans to Black-owned firms are also more likely to trigger the other criteria. For example, since Black-owned firms are likely to be smaller, they are more likely to operate out of an apartment building, and thus fall into suspicious loan criterion (2). Criterion (3) flags loans with implied compensation per job reported that is at least three times the industry average. However, since the maximum loan per job allowed under PPP is $100,000, Griffin et al. (2021) note that "this flag is only possible in industry-CBSA pairs with average annual compensation/receipts below $33,333.33." Of course, these low-paying industries are more likely to have small businesses that are Black-owned.

In sum, there are strong reasons to think the Griffin suspicious loan index is highly correlated with extending even non-fraudulent loans to Black-owned firms. This dramatically complicates our ability to interpret any observed correlation between share of loans to Black-owned firms and the suspicious loan index as the causal effect of lending standards.

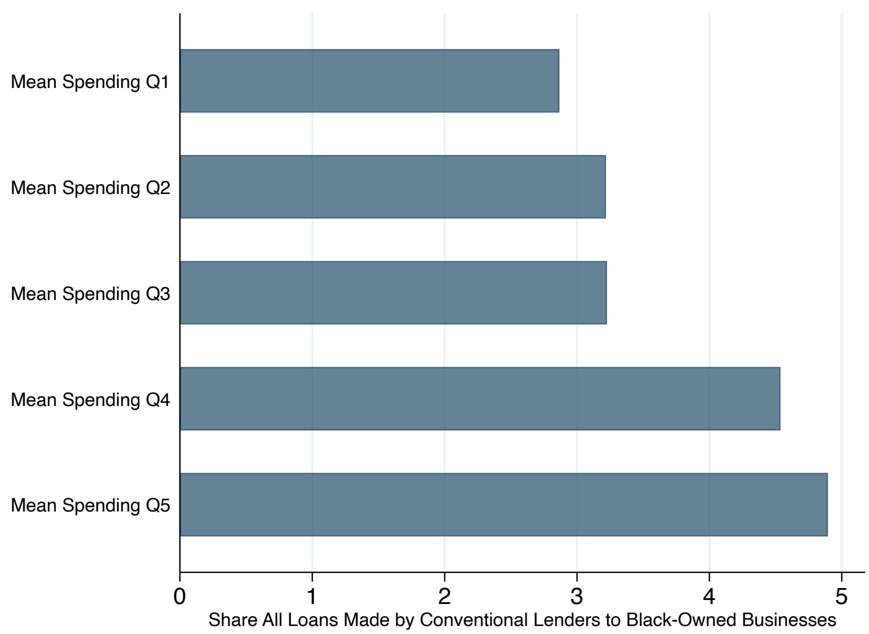
Small Banks vs. Large Banks. One other key reason reduces the plausibility of racial differences in the propensity to commit fraud being a good explanation for our findings. Specifically, we would not expect concerns about fraud to be particularly prevalent at small banks, the banks with the lowest share of PPP loans to Black-owned firms. In fact, it is the larger banks (and in particularly the top-4 banks) that are the most intensively regulated and have the most advanced compliance systems (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.

Figure A.1: **Branch-Level Software Spending as Proxy for Automation**

(A) Branch-Level Software Spending 2017-2019 by Lender Type (No HQ)

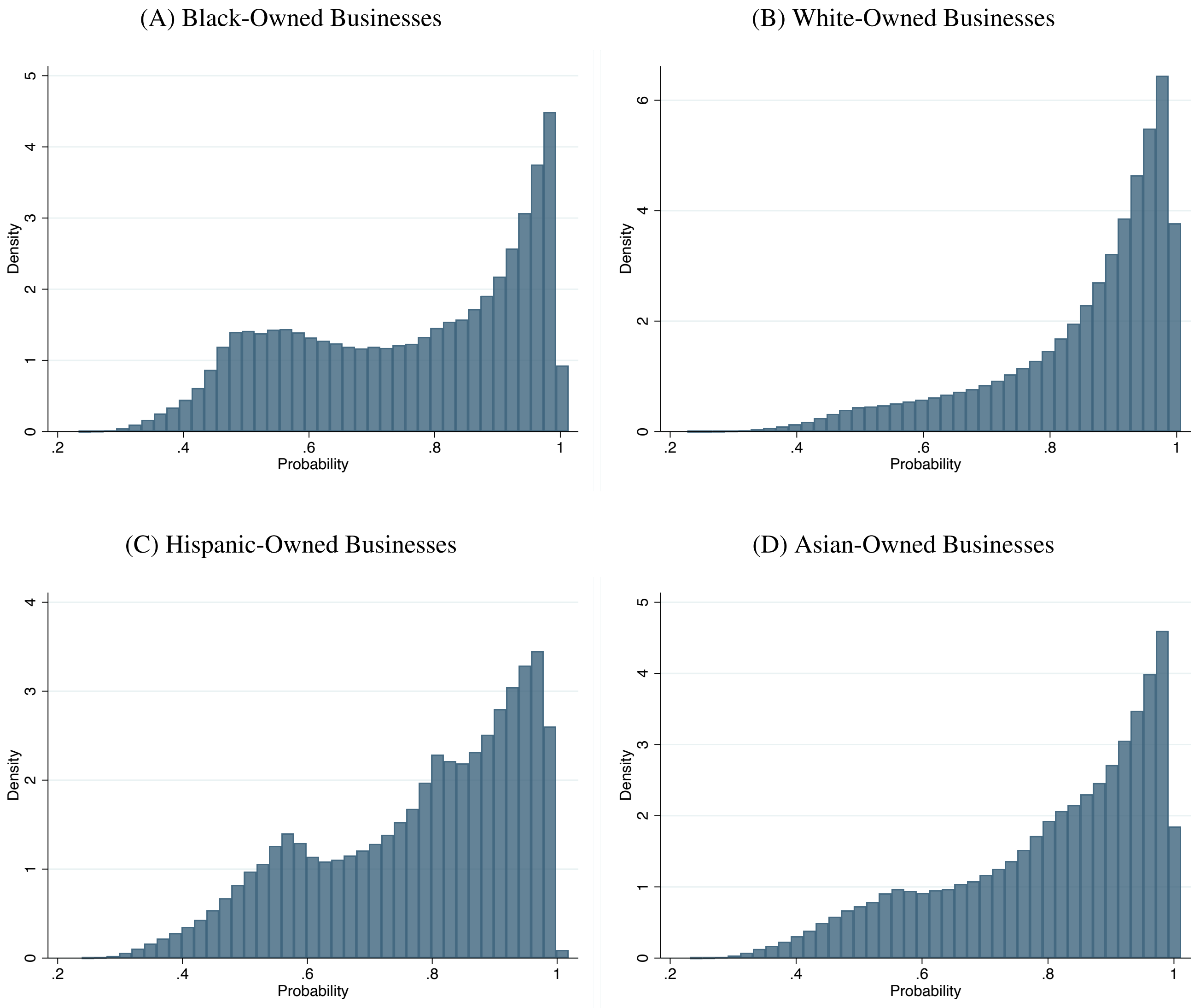


(B) Share of PPP Loans to Black-Owned Businesses by Branch-Level Software Spending



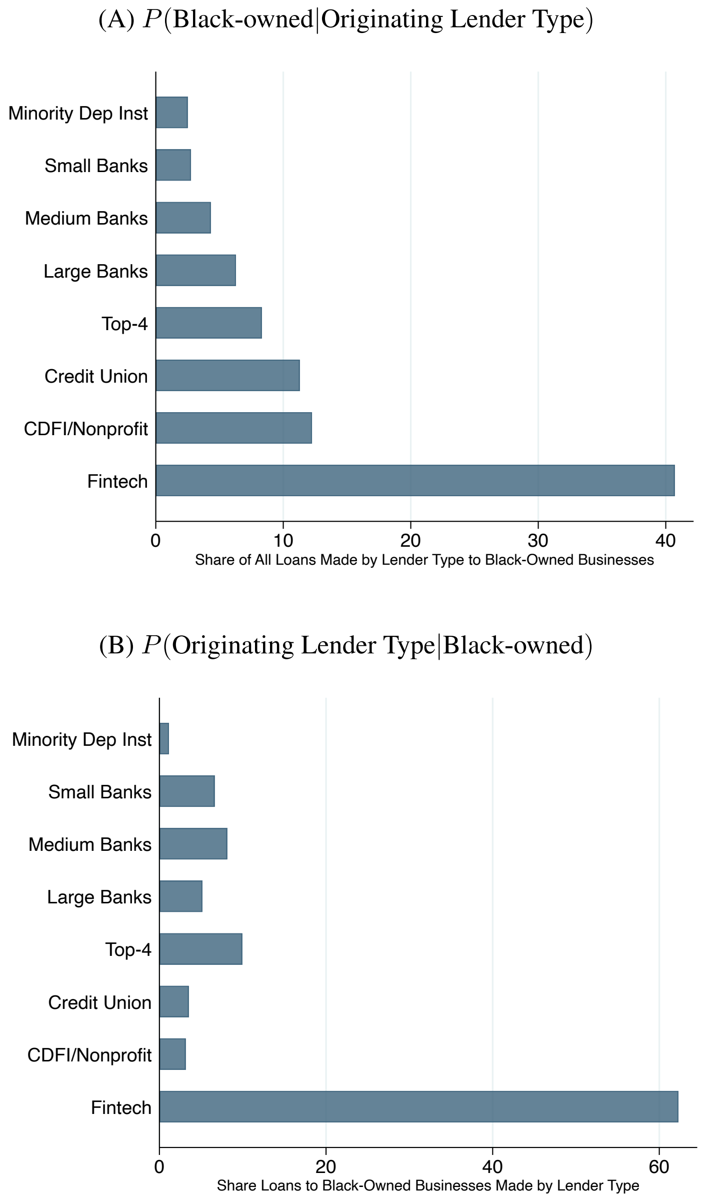
Note: Panel A shows the mean branch software spending from 2017-2019 by lender type, excluding lender headquarters, for all banks in the bank IT spending data matched to PPP lenders. This is a measure of automation for the bank branches of the lender. The box represents the 75th, 50th, and 25th percentiles. The upper and lower whiskers represent the upper and lower adjacent values, respectively. The data are at the branch level. For Panel B, we split banks into quintiles based on their average branch-level software spending, and then plot the share of PPP loans to Black-own firms for each of the quintiles.

Figure A.2: **Race Probability Distributions**



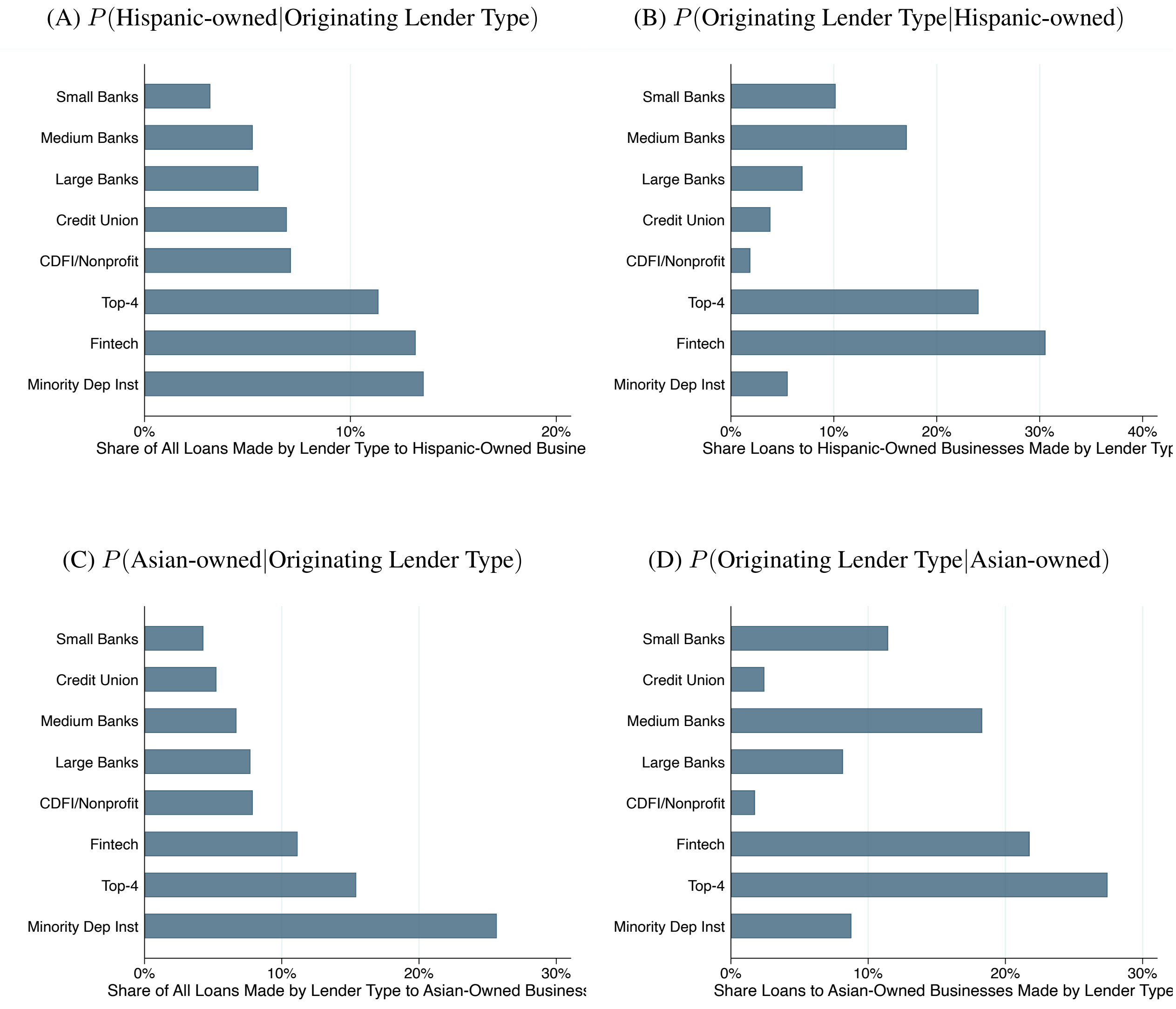
Note: This figure shows the probability distribution for each race/ethnicity generated by our algorithm. Specifically, each graph contains the sample of borrowers predicted by the algorithm to be the particular race/ethnicity, which means that the race/ethnicity has the highest probability. For example, 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.3: **Black-Owned Business PPP Lending by Institution Type (Self-Reported)**



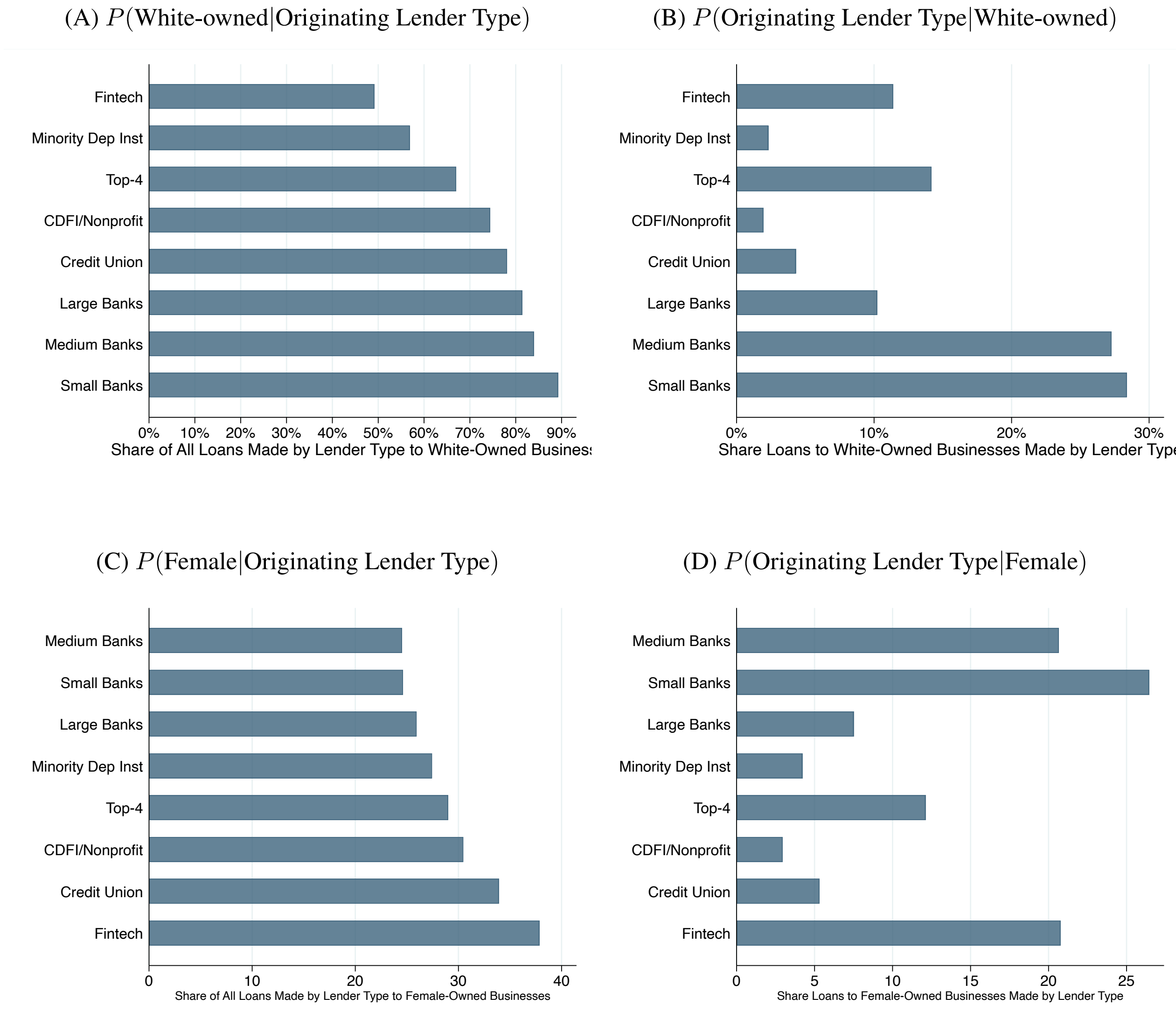
Note: This figure shows shares of PPP loans made to businesses that self-identify as Black-owned by lender type. The sample is limited to the 1,098,682 businesses for which the data include self-reported race.

Figure A.4: **PPP Lending to Hispanic and Asian-owned Businesses by Institution Type**



Note: This figure shows the shares of PPP loans made by originating lender type to Hispanic- (Panels A and B) and Asian- (Panels C and D) owned businesses. Panels A and C show the Hispanic and Asian share of PPP loans made by originating lender type. Panels B and D show the shares of PPP loans from originating lender type made to Hispanic- and Asian-owned businesses.

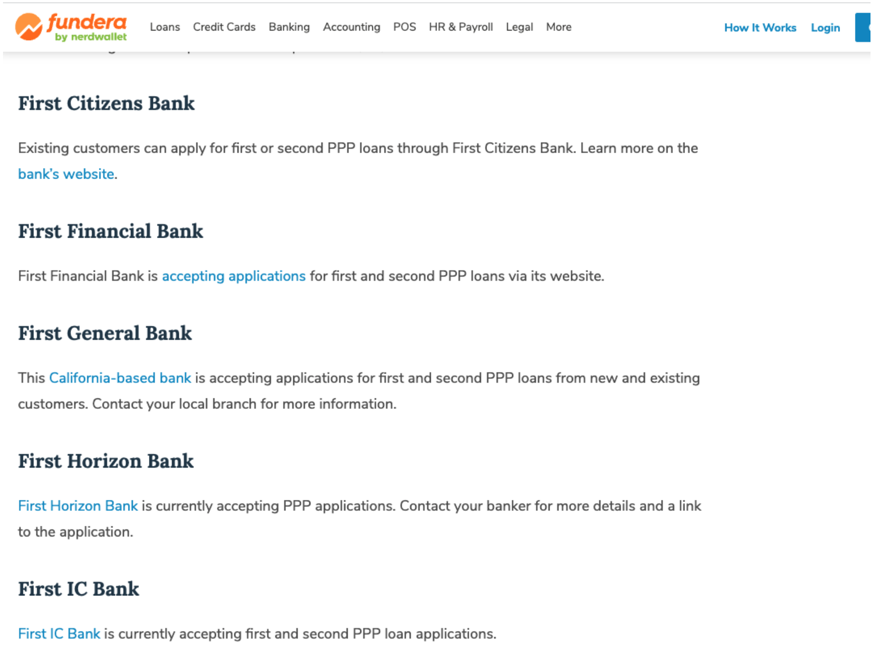
Figure A.5: **PPP Lending to White and Female-owned Businesses by Institution Type (Continued)**



Note: This figure shows the shares of PPP loans made by originating lender type to White- (Panels A and B) and Female- (Panels C and D) owned businesses. Panels A and C show the White and Female share of PPP loans made by originating lender type. Panels B and D show the shares of PPP loans from originating lender type made to White- and Female-owned businesses.

Figure A.6: **Examples of Lenders Accepting PPP Applications Online**

(A) Fundera Screenshot 1



fundera by nerdwallet Loans Credit Cards Banking Accounting POS HR & Payroll Legal More How It Works Login

First Citizens Bank

Existing customers can apply for first or second PPP loans through First Citizens Bank. Learn more on the bank's website.

First Financial Bank

First Financial Bank is accepting applications for first and second PPP loans via its website.

First General Bank

This California-based bank is accepting applications for first and second PPP loans from new and existing customers. Contact your local branch for more information.

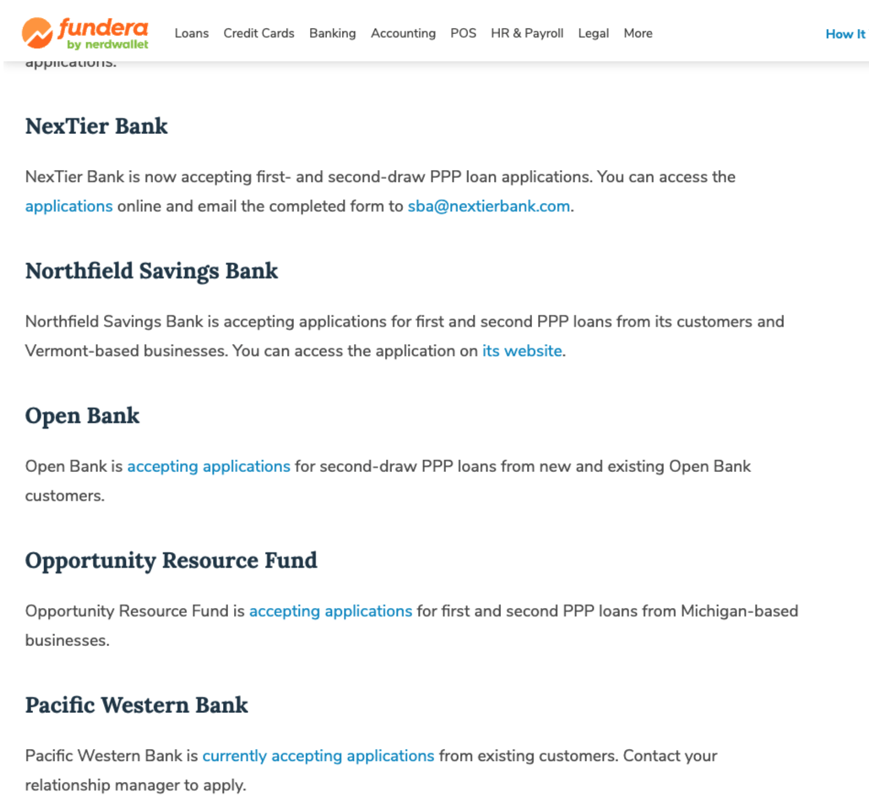
First Horizon Bank

First Horizon Bank is currently accepting PPP applications. Contact your banker for more details and a link to the application.

First IC Bank

First IC Bank is currently accepting first and second PPP loan applications.

(B) Fundera Screenshot 2



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applications.

NexTier Bank

NexTier Bank is now accepting first- and second-draw PPP loan applications. You can access the applications online and email the completed form to sba@nextierbank.com.

Northfield Savings Bank

Northfield Savings Bank is accepting applications for first and second PPP loans from its customers and Vermont-based businesses. You can access the application on its website.

Open Bank

Open Bank is accepting applications for second-draw PPP loans from new and existing Open Bank customers.

Opportunity Resource Fund

Opportunity Resource Fund is accepting applications for first and second PPP loans from Michigan-based businesses.

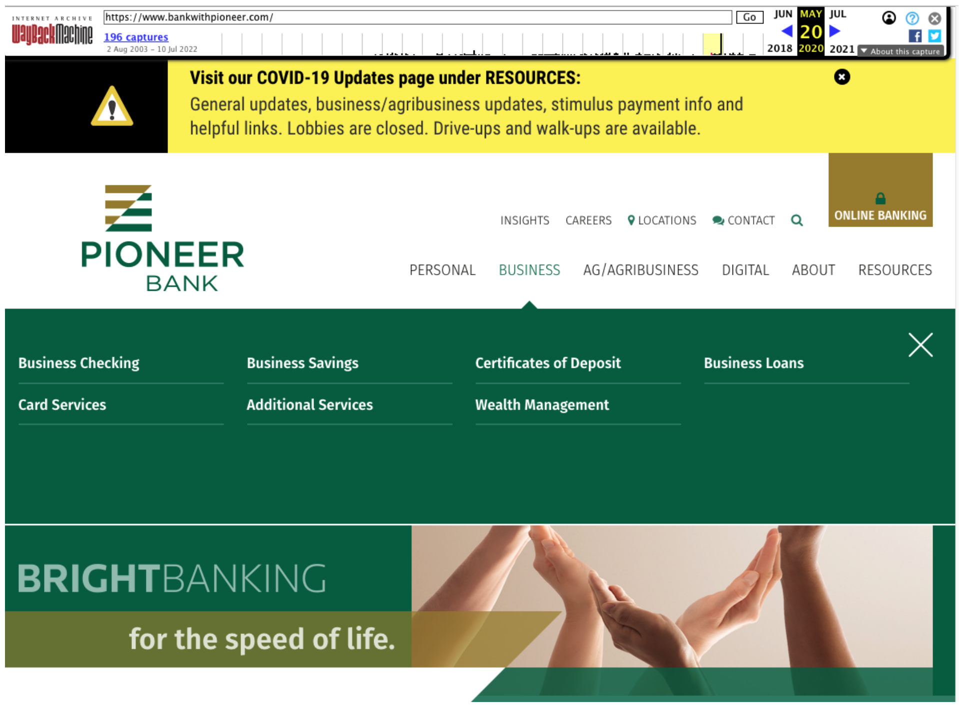
Pacific Western Bank

Pacific Western Bank is currently accepting applications from existing customers. Contact your relationship manager to apply.

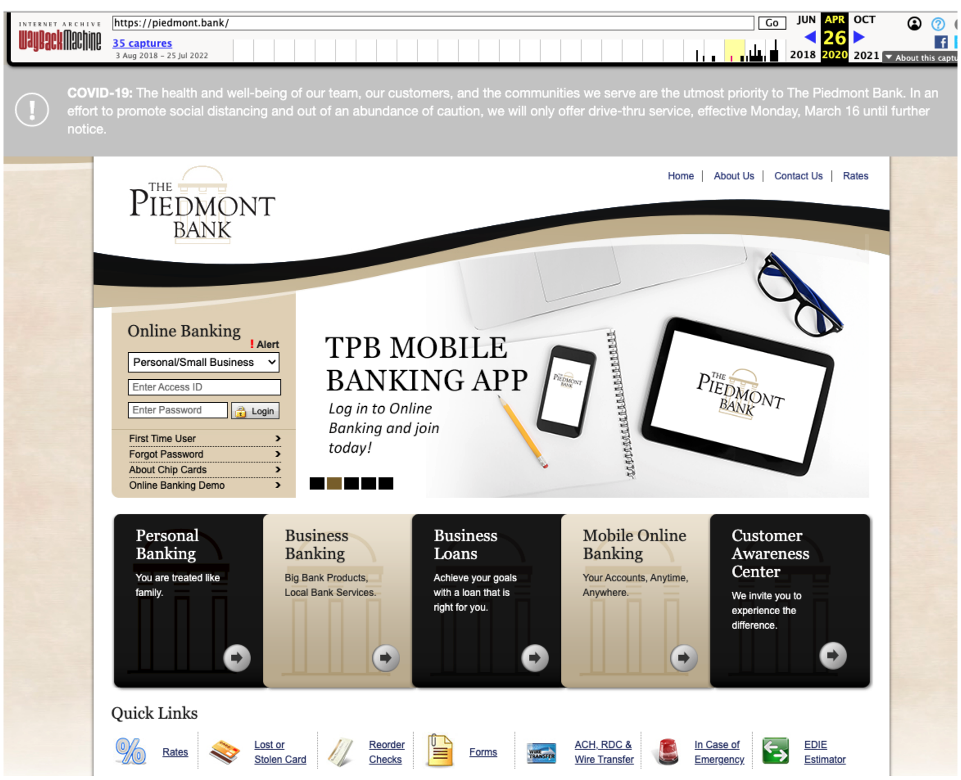
Note: This figure shows screenshots of an alphabetically organized list from 2020 of lenders accepting PPP applications online.

Figure A.7: **Examples of Small Banks with Reduced In-Person Service due to Covid**

(A) Pioneer Bank Website, April 2020



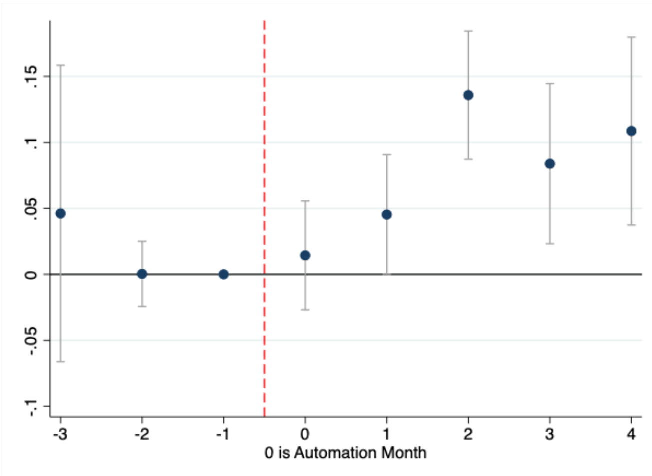
(B) Piedmont Bank Website, May 2020



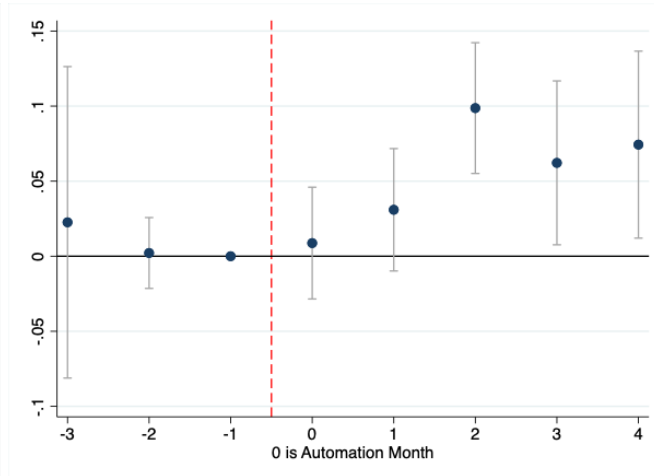
Note: This figure shows screenshots of two small banks' websites (Pioneer Bank in Minnesota and Piedmont Bank in Georgia) available from the Wayback Internet Archive for the height of small bank PPP lending in April and May of 2020. The banners at the top describe at most drive-up service.

Figure A.8: **Effect of Automation during PPP on Lending to Black-Owned Small Businesses (Self-Identified)**

(A) Simple Differences-in-Differences

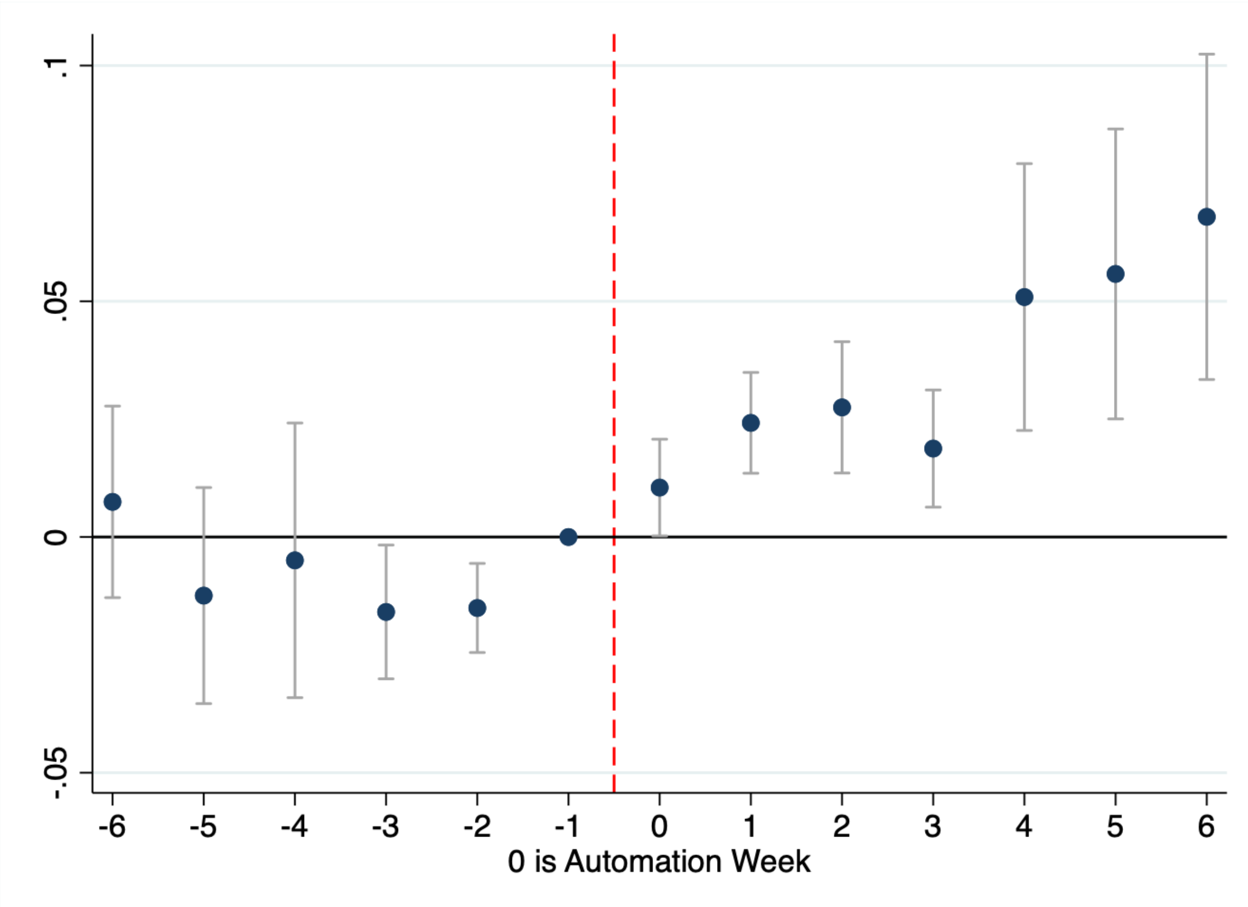


(B) With Additional Controls



Note: This figure reports dynamic differences-in-differences estimates at the monthly level, using Equation 1. The sample is limited to the subset of loans for which race/ethnicity is self-reported, and uses self-reported race/ethnicity of the borrower as the dependent variable instead of predicted race/ethnicity. 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 5, Panel A, column 2. 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 months prior to automation. Standard errors are clustered by zip code. The grey bars represent 95% confidence intervals.

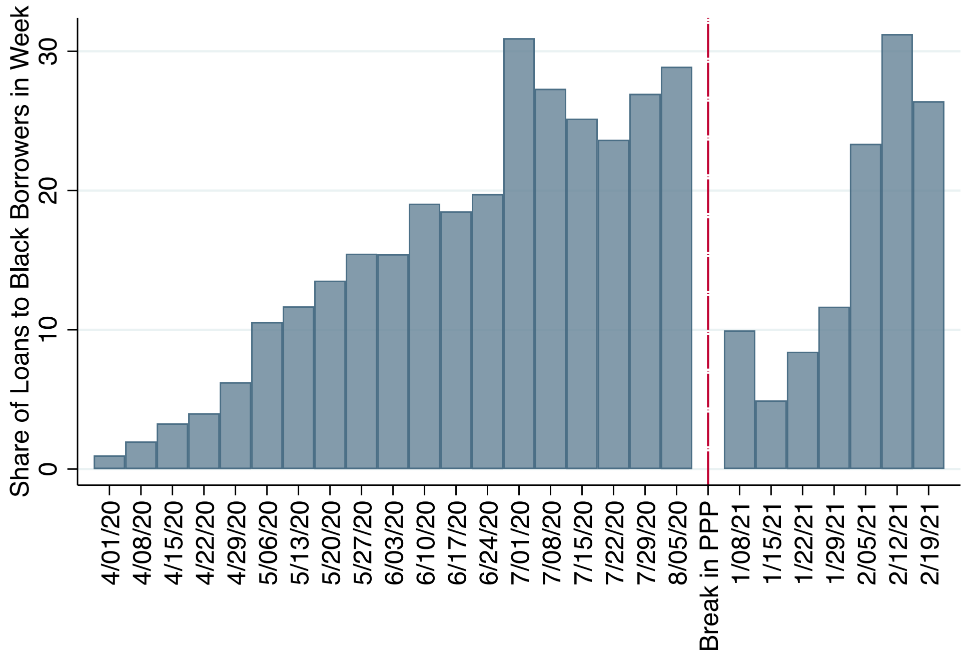
Figure A.9: **Weekly Balanced Sample Event Study for the Share of Loans to Black-Owned Businesses Before and After Small Bank Automation**



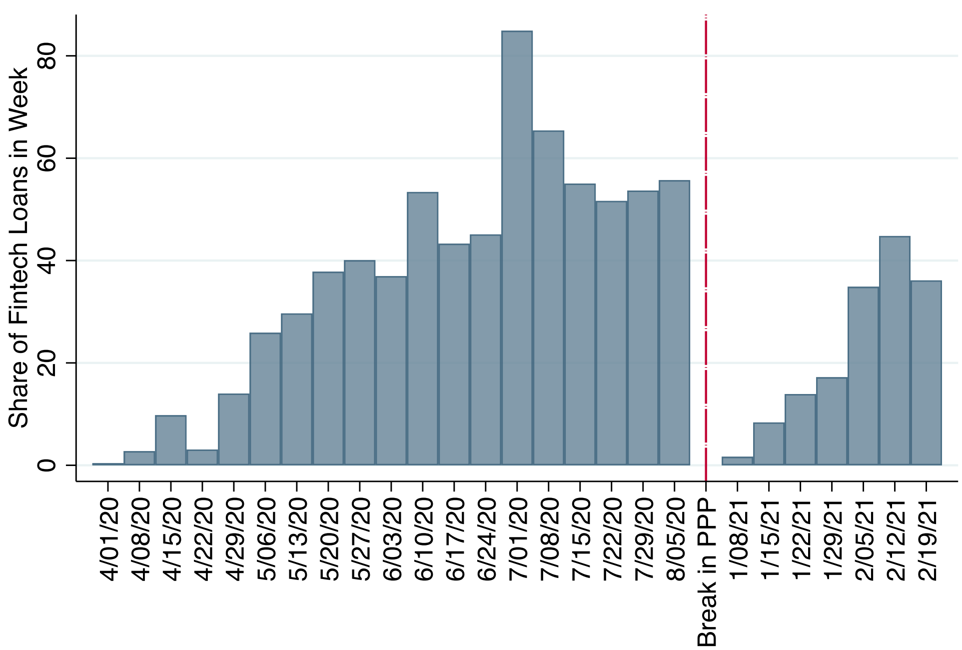
Note: This figure reports dynamic differences-in-differences estimates, using Equation 1. We study a weekly balanced panel that includes automating banks that have observations at least six weeks on both sides of the automation date. We include bank and time fixed effects (as in Table 5 Panel A column 2). Standard errors are clustered by zip code. The grey bars represent 95% confidence intervals.

Figure A.10: **Black-Owned Businesses PPP Lending by Week**

(A) Black-Owned Businesses PPP Lending by Week

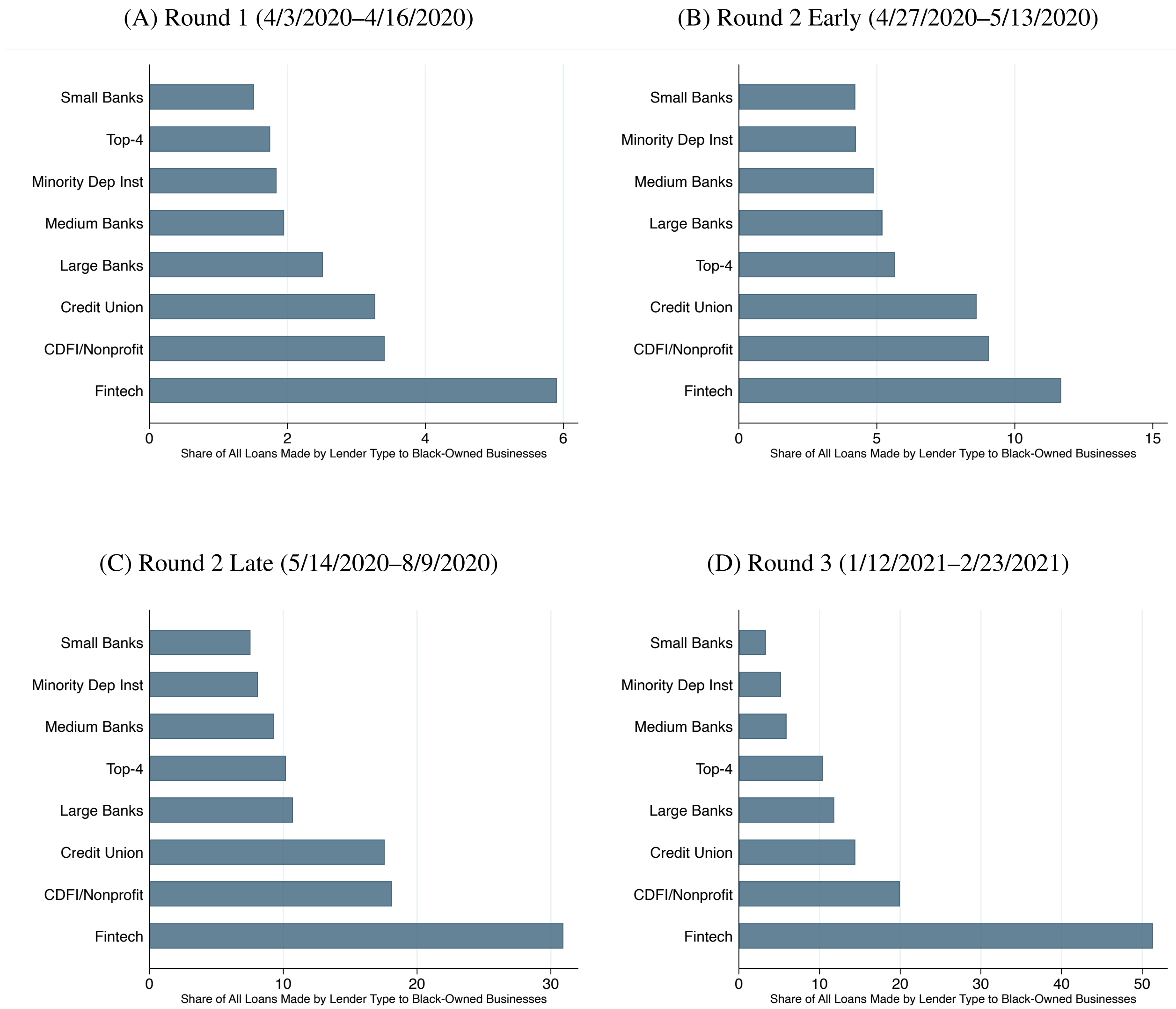


(B) Fintech PPP Lending by Week



Note: This figure shows the 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.

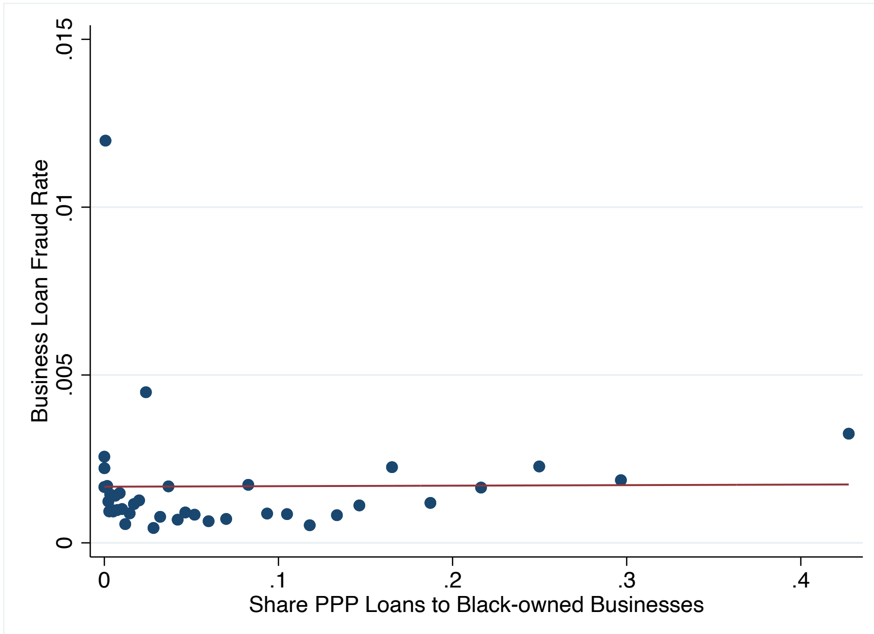
Figure A.11: **Black-Owned Business PPP Lending by Institution Type and Round**



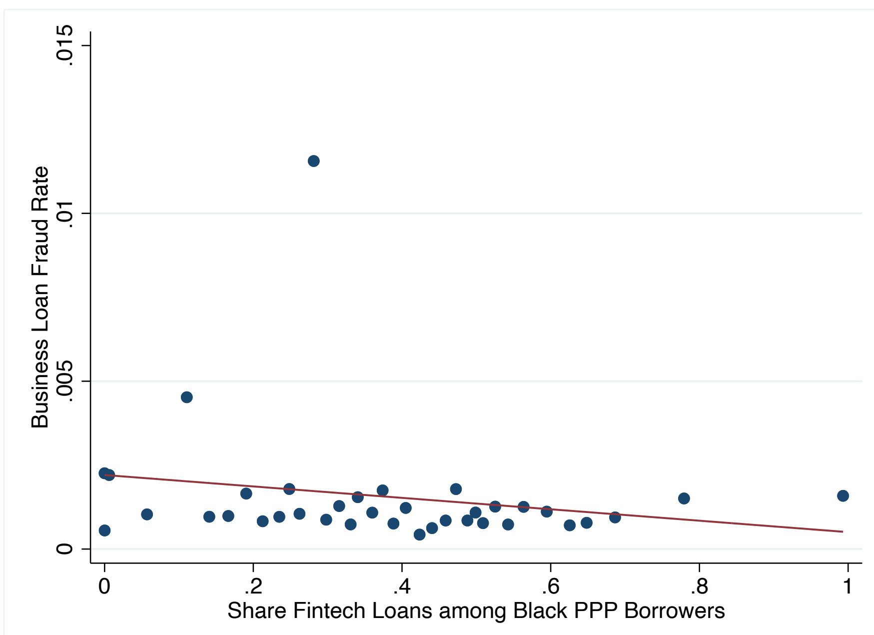
Note: This figure shows the share of PPP loans made by originating lender type to Black-owned businesses by PPP round. Panel A limits the sample to Round 1 PPP approvals. Panel B limits the sample to Round 2 early approvals. Panel C limits the sample to Round 2 late approvals. We distinguish Round 2 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.12: **County-Level Loan Fraud and Fintech Lending to Black-owned Firms**

(A) Loan Fraud Rate vs. Share of PPP Loans to Black-Owned Firms



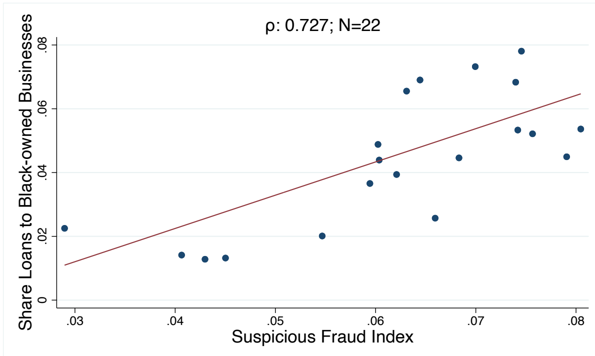
(B) Loan Fraud Rate vs. Fintech Share of PPP Loans Among Black-Owned Borrowers



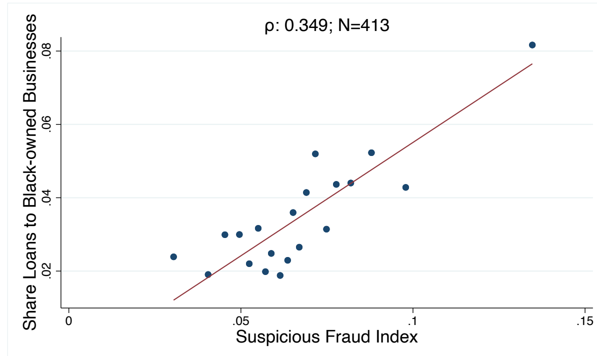
Note: This figure shows binscatter plots exploring the relationship between small business lending to Black-owned firms and small business loan fraud. All data are at the county level. In both panels, the vertical axis is the number of small business loan Suspicious Activity Reports (SARs) in 2020 divided by the total number of small business loans in 2020. SAR data is from FinCEN, and data on the total number of loans is from CRA disclosures. In Panel A, the horizontal axis shows the share of PPP loans to Black-owned firms in that county. In Panel B, the horizontal axis shows the share of PPP loans to Black-owned borrowers made by fintech lenders.

Figure A.13: **Griffin Suspicious PPP Lender Index and Share of PPP Loans to Black-Owned Firms**

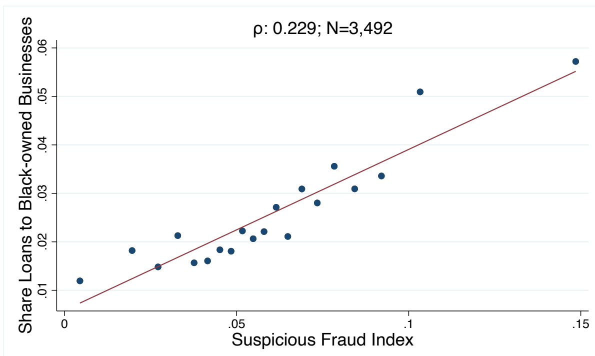
(A) Large Banks, Including Top-4



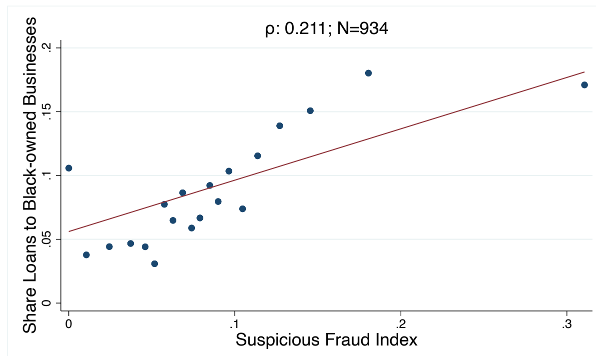
(B) Medium Banks



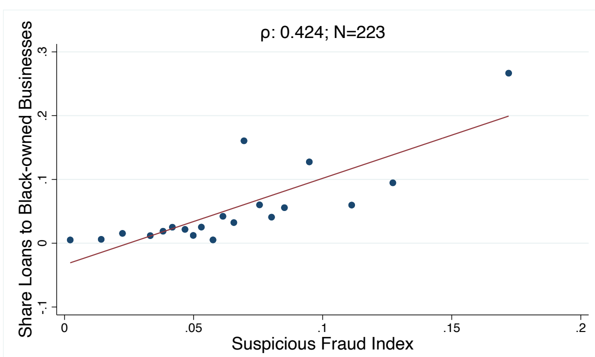
(C) Small Banks



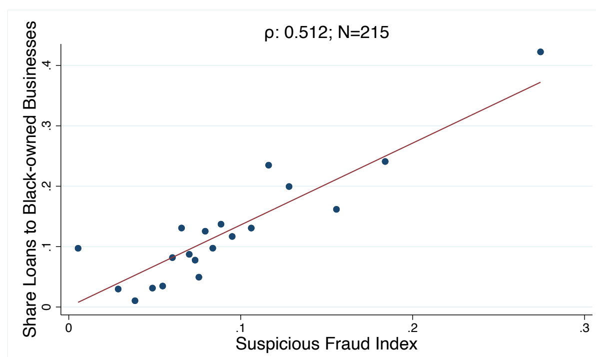
(D) Credit Unions



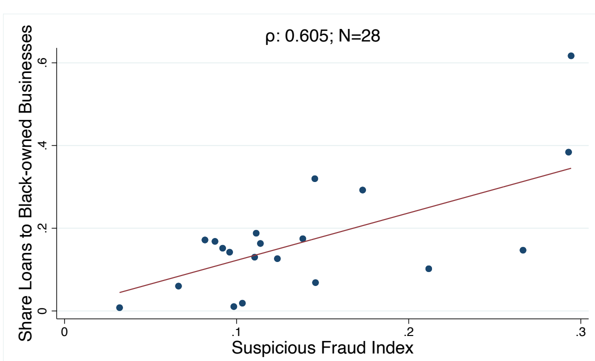
(E) Minority Depository Institutions



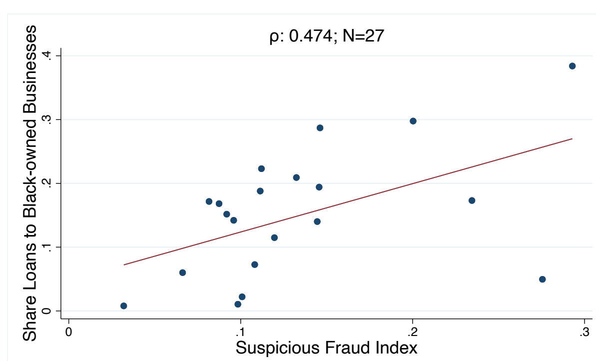
(F) CDFIs/Nonprofits



(G) Fintechs

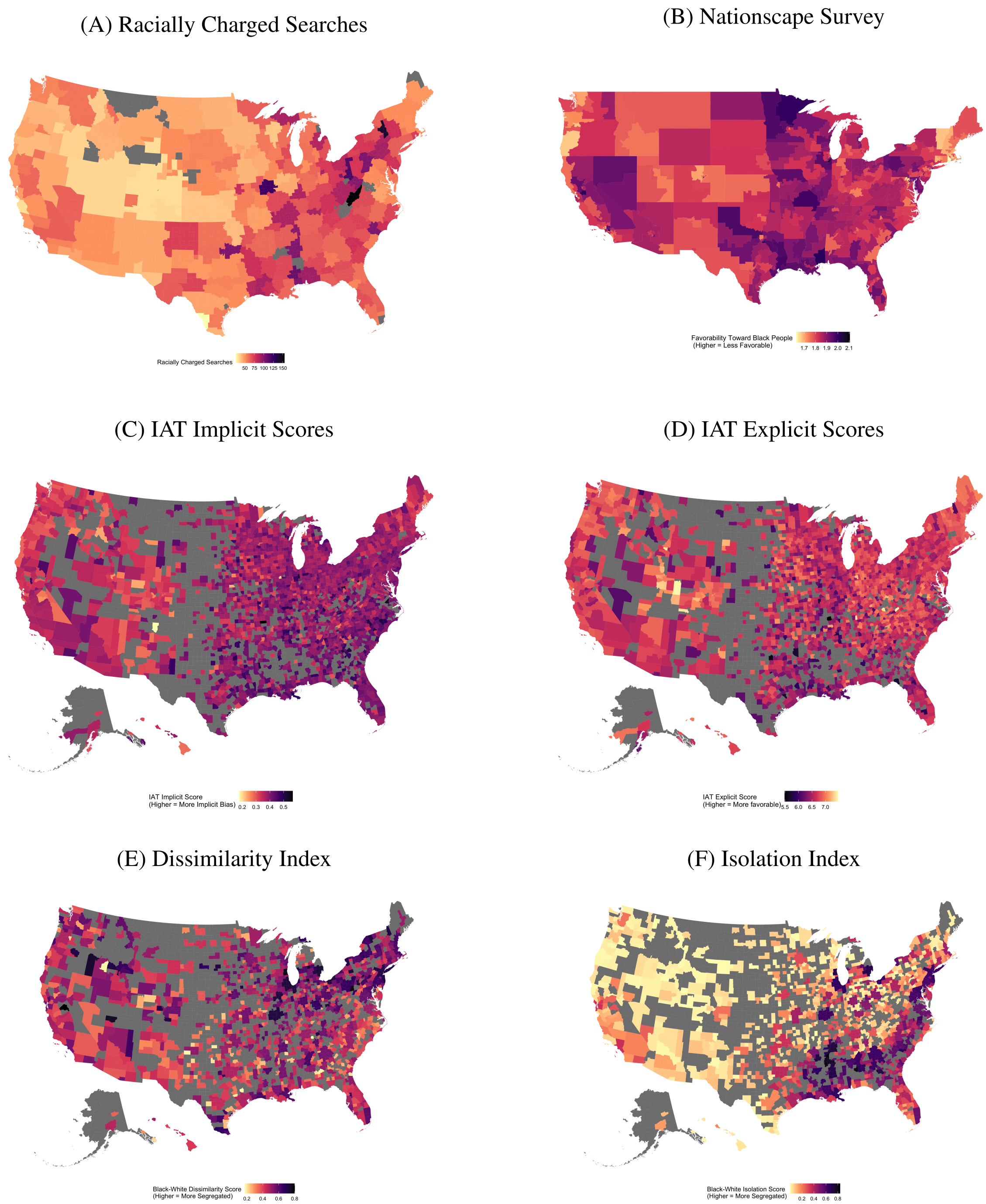


(H) Fintechs, Exlcuding Itria Ventures



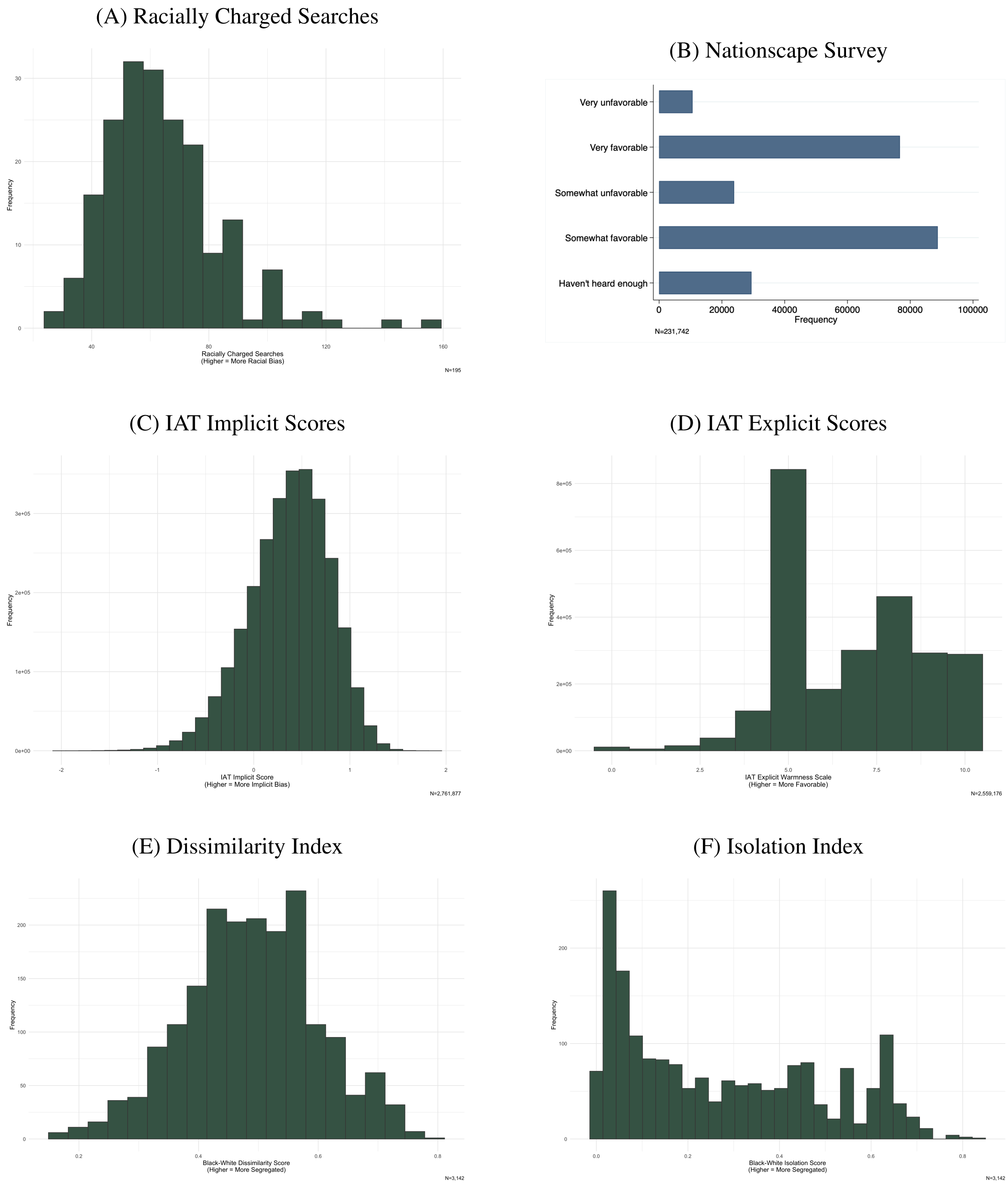
Note: This figure contains binscatters documenting the relationship between the lender-level suspicious lending index from Griffin et al. (2021) index and the lender's share of PPP loans to Black-owned firms. The binscatters separately consider each lender type. The data are at the originating lender level.

Figure A.14: **Geographical Distribution of Racial Animus**



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.15: **Distribution of Racial Animus**



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.

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 without Predicted Race

Panel A: All First Draw PPP Loans Before Feb 24th without Race Prediction

	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
Top-4	4	869,976	15.3%	69.2	79,575	5,000	21,432	144,289
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 B: Bank and Credit Relationships Sample without 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	216,240	28.5%	14.2%	79.8%	9,124	-36,671	1,374	62,879
Top-4	37,731	67.9%	15.6%	87.3%	12,019	-48,003	2,768	86,449
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 loan is assigned to a single type. The sample is restricted to firms without a race prediction. In Panel B, the second 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 statements.

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 size 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 Panels A and B, the percents represent the percent of total observations in the sample. Panel C contains summary statistics about the probability distributions by predicted race/ethnicity.

Table A.4: 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%
Top-4	15.9%	79,901	15.4%	6.2%	11.4%	67.0%
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%
Top-4	17.6%	72,738	13.6%	8.4%	14.4%	63.6%
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 = 278,404

	Share Loans	Mean Loan Amt ($)	Share Asian Appl	Share Black Appl	Share Hisp Appl	Share White Appl
All	100%	58,769	11.4%	12.3%	10.8%	65.5%
Sent to Lender:						
Only Fintech	56.7%	35,634	12.3%	13.7%	10.4%	63.6%
Only Conventional	26.9%	101,304	8.7%	9.5%	11.6%	70.1%
Both	16.4%	68,932	12.5%	12.0%	11.0%	64.4%
PPP Loan from:						
Conventional	29.3%	89,368	10.6%	7.0%	9.0%	73.3%
Fintech	31.1%	43,193	11.5%	15.8%	10.1%	62.5%
No PPP Loan	39.6%	48,323	11.8%	13.4%	12.6%	62.1%

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%
Top-4	17.3%	104,292	25.4%	3.6%	10.9%	60.0%
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 Ocrolus 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 applications-matched sample. We limit the Lendio sample to applications sent to at least one lender by Lendio. The loan amount is the actual PPP loan amount except for the "No PPP Loan" category, in which case it is the amount sought as reported by Lendio. Panel D restricts to the Enigma card revenue-matched sample. We limit the Enigma sample to borrowers for whom we observe card revenue prior to loan approval.

Table A.5: Additional Sample Characteristics

	Full PPP Sample N = 5,692,097		PPP Analysis Sample N = 4,183,623		Matched to Ocrolus N = 168,360	
	Mean	P50	Mean	P50	Mean	P50
Lender Type						
Top 4	15.3%		15.9%		17.6%	
Large Banks	10.4%		9.4%		9.0%	
Medium Banks	24.7%		24.3%		16.9%	
Small Banks	23.9%		23.9%		12.6%	
Credit Union	4.0%		4.1%		3.4%	
CDFI/Nonprofit	2.0%		2.0%		1.8%	
Minority Dep Inst	3.5%		3.0%		2.4%	
Fintech	16.2%		17.4%		36.3%	
Borrower Firm Business Type						
Corporation	27.0%		27.8%		31.6%	
LLC	28.9%		26.8%		31.6%	
Other	11.8%		11.9%		9.8%	
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 ($)	93,784	20,833	93,666	20,833	80,897	21,121
Borrower Firm Industry						
Professional/Technical Services	12.6%		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	5.3%		5.2%		3.0%	
Middle Atlantic	12.5%		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	19.5%		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, the 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.6: 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%
Top-4	18.4%	104,212	17.0%	3.4%	11.7%	67.9%
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%
Top-4	11.6%	11,923	10.9%	13.9%	10.7%	64.5%
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.7: Summary Statistics on Branch Software Spending

	N	Mean	P50	SD
Number of Unique Banks				
All	3,381			
Top 4 Banks	4			
Large Banks	16			
Medium Banks	396			
Small Banks	2,965			
Branch Software Spending 2017-2019 (No HQ)				
All	106,776	61,452	36,385	80,154
Top 4 Banks	29,849	70,160	58,455	77,060
Large Banks	24,679	57,733	36,385	74,010
Medium Banks	31,816	62,022	32,342	90,099
Small Banks	20,432	52,337	29,858	73,706
Borrower-Matched Branch Software Spending 2017-2019 (No HQ)				
All	2,890,666	76,093	52,359	100,812
Top 4 Banks	665,422	87,615	73,069	83,892
Large Banks	361,043	66,923	48,712	89,226
Medium Banks	966,552	83,470	49,977	116,888
Small Banks	897,649	63,298	36,249	96,136

Note: This table shows summary statistics on average bank branch software spending from 2017-2019 by bank lender type, using data from SWZD.

Table A.8: 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								
Top-4	2.8%		28.7%		11.6%		4.2%	
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	
Self-Employed	13.0%		24.8%		52.8%		75.3	
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 industries, and code the rest as "Other."

Table A.9: Fintech PPP Loans and the Zip Code's Black Share of Population

Dependent Variable:	𝟙(Fintech)			
Sample of Borrowers:	All		Black	White
	(1)	(2)	(3)	(4)
𝟙(Black-Owned)	0.159***	0.131***		
	(0.002)	(0.002)		
Black Pop. Share in Zip		0.125***	0.089***	0.078***
		(0.004)	(0.004)	(0.004)
Approval Week FE	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes
State 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 2, 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.10: Business Owner Race and PPP Lender Type

Dependent Variable:	𝟙(Fintech)		𝟙(Top-4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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)
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)
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)
Approval Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan Amount FE	No	Yes	No	Yes	No	Yes	No	Yes
Zip Code 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 2 for indicators for whether the originating lender is a Fintech (columns 1–2), Top-4 bank (columns 3–4), large bank (columns 5–6), and small/medium-sized bank (columns 7–8). Here, Black-owned businesses represent the single omitted group, so the coefficients should be interpreted relative to them. Controls are as described in Table 4. Standard errors are clustered by borrower zip code. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.11: Self-Reported Business Owner Race and PPP Lender Type

Panel A: Fintech PPP Loan

Dependent Variable:	𝟙(Fintech)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(SelfID Black-Owned)	0.507***	0.330***	0.299***	0.245***	0.279***	0.320***	0.186***
	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.002)
Approval Week FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	No	No	Yes	No	No	No	Yes
Zip Code FE	No	No	No	Yes	No	No	Yes
Industry FE	No	No	No	No	Yes	No	Yes
Business Type FE	No	No	No	No	No	Yes	Yes
Employer Status FE	No	No	No	No	No	Yes	Yes
Dep Var Mean	0.173	0.173	0.173	0.173	0.173	0.173	0.173
R^2	0.181	0.328	0.342	0.405	0.374	0.347	0.459
Observations	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:	𝟙(Top-4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)
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)
Approval Week FE	No	Yes	No	Yes	No	Yes
Loan Amount FE	No	Yes	No	Yes	No	Yes
Zip Code 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)
Approval Week FE	No	Yes	No	Yes	No	Yes	No	Yes
Loan Amount FE	No	Yes	No	Yes	No	Yes	No	Yes
Zip Code 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 2. 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 7 with dependent variables for whether the lender is a top-4 bank (columns 1–2), large bank (columns 3–4), or small/medium-sized bank (columns 5–6). 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. 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.12: Effect on Automation during PPP on Lending to Black-Owned Small Businesses (Self-Identified)

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

Dependent Variable:	𝟙(Self-ID Black-Owned)		𝟙(Owned by Self-ID:) Hispanic	Asian	White
	(1)	(2)	(3)	(4)	(5)
𝟙(After Automation)	0.075***	0.057***	-0.002	0.007	-0.061***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.010)
Bank FE	Yes	Yes	Yes	Yes	Yes
Approval Week FE	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	No	Yes	Yes	Yes	Yes
Business Type FE	No	Yes	Yes	Yes	Yes
Zip Code FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
Employer Status FE	No	Yes	Yes	Yes	Yes
Dep Var Mean	0.035	0.035	0.076	0.079	0.811
Observations	535,209	535,209	535,209	535,209	535,209

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

Dependent variable:	𝟙(Self-ID Black-Owned)					
	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(After Automation)	0.054***	0.056***	0.058***	0.056***	0.048***	0.055***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
𝟙(After Automation) × Racial Animus	0.016***	0.016***	0.006	0.010*	0.045***	0.003
	(0.005)	(0.005)	(0.004)	(0.006)	(0.004)	(0.004)
Racial Animus Measure	IAT (Implicit)	IAT (Explicit)	Stephens-Davidowitz	Nationscape	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	0.035	0.035	0.035	0.035	0.035	0.035
Observations	535,209	535,209	535,209	535,209	535,209	535,209

Note: This table reports estimates of Equation 3, using the sample of PPP loans extended by small and medium banks for which race/ethnicity is self-reported. This table uses the self-reported race/ethnicity of the borrower as the dependent variable instead of the predicted race/ethnicity. Columns 1-2 of Panel A show the effect of automation on the probability that a loan is extended to a Black-owned business. 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 measures of local racial animus (from Table 6), 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 Table 4. Standard errors are clustered by zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.13: Signal Strength of Black Business Ownership and PPP Lender Type

Panel A: Fintech PPP Loan

Dependent Variable:	$\mathbb{1}$(Fintech)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}$(Black Owned–First Quintile)	0.188***	0.111***	0.097***	0.085***	0.090***	0.096***	0.043***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\mathbb{1}$(Black-Owned–Second Quintile)	0.252***	0.157***	0.141***	0.135***	0.132***	0.136***	0.080***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\mathbb{1}$(Black-Owned–Third Quintile)	0.359***	0.234***	0.211***	0.205***	0.199***	0.203***	0.127***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
$\mathbb{1}$(Black-Owned–Fourth Quantile)	0.521***	0.353***	0.321***	0.315***	0.304***	0.302***	0.193***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
$\mathbb{1}$(Black-Owned–Fifth Quintile)	0.663***	0.470***	0.426***	0.405***	0.400***	0.411***	0.247***
	(0.006)	(0.005)	(0.004)	(0.003)	(0.006)	(0.006)	(0.003)
Approval Week FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	No	No	Yes	No	No	No	Yes
Zip Code FE	No	No	No	Yes	No	No	Yes
Industry FE	No	No	No	No	Yes	No	Yes
Business Type FE	No	No	No	No	No	Yes	Yes
Employer Status FE	No	No	No	No	No	Yes	Yes
Dep Var Mean	0.174	0.174	0.174	0.174	0.174	0.174	0.174
R^2	0.104	0.237	0.248	0.283	0.273	0.280	0.359
Observations	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–First Quintile)	0.018***	-0.002	-0.012***	-0.007***	-0.198***	-0.031***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
$\mathbb{1}$(Black-Owned–Second Quintile)	-0.014***	-0.007***	-0.019***	-0.015***	-0.227***	-0.059***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
$\mathbb{1}$(Black-Owned–Third Quintile)	-0.038***	-0.009***	-0.035***	-0.026***	-0.286***	-0.086***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
$\mathbb{1}$(Black-Owned–Fourth Quintile)	-0.086***	-0.013***	-0.056***	-0.041***	-0.365***	-0.123***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
$\mathbb{1}$(Black-Owned–Fifth Quintile)	-0.126***	-0.012***	-0.072***	-0.058***	-0.432***	-0.152***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)	(0.003)
Approval Week FE	No	Yes	No	Yes	No	Yes
Loan Amount FE	No	Yes	No	Yes	No	Yes
Zip Code 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 2. 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 A.14: 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)
Approval Week FE	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes
Zip Code 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 2, specifically replicating the specification in Table 4, column 7 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.15: Black Business Ownership and PPP Lender Type – Employer Firms Only

Panel A: Fintech PPP Loan

Dependent Variable:	𝟙(Fintech)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	0.186***	0.112***	0.107***	0.087***	0.110***	0.107***	0.075***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Approval Week FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	No	No	Yes	No	No	No	Yes
Zip Code FE	No	No	No	Yes	No	No	Yes
Industry FE	No	No	No	No	Yes	No	Yes
Business Type FE	No	No	No	No	No	Yes	Yes
Employer Status FE	No	No	No	No	No	Yes	Yes
Dep Var Mean	0.174	0.174	0.174	0.174	0.174	0.174	0.174
R^2	0.011	0.114	0.117	0.141	0.136	0.129	0.177
Observations	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:	𝟙(Top-4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)
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)
Approval Week FE	No	Yes	No	Yes	No	Yes
Loan Amount FE	No	Yes	No	Yes	No	Yes
Zip Code 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	0.184	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 2 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 7 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.16: Alternative Fixed Effects

	Analysis Sample					Employer Sample				
Dependent Variable:	𝟙(Fintech)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
𝟙(Black-Owned)	0.228***	0.231***	0.199***	0.173***	0.150***	0.106***	0.100***	0.101***	0.077***	0.052***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Approval Week FE	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
Loan Amount FE	Yes	No	No	No	No	Yes	No	No	No	No
Census Tract FE	No	Yes	No	No	No	No	Yes	No	No	No
Industry FE	No	No	Yes	No	No	No	No	Yes	No	No
Zip Code $\times$ Industry FE	No	No	No	Yes	No	No	No	No	Yes	No
Zip Code $\times$ Approval Week FE	No	No	No	No	Yes	No	No	No	No	Yes
Dep Var Mean	0.174	0.174	0.174	0.174	0.174	0.174	0.174	0.174	0.174	0.174
R^2	0.248	0.257	0.305	0.380	0.376	0.119	0.134	0.179	0.270	0.243
Observations	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	2,653,490	2,653,490	2,653,490	2,653,490	2,653,490

Note: This table reports estimates of Equation 2. Columns 1–5 use the main analysis sample and columns 6–10 use the employer-only sample. Columns 1 and 6 use a finer binning of loan amount into 1000 bins. Columns 2 and 7 use census tract fixed effects instead of zip code fixed effects. Columns 3 and 8 use 6-digit NAICS industry codes. Columns 4 and 9 interact 3-digit NAICS with borrower zip code. Columns 5 and 10 interact approval week with borrower zip code.

Table A.17: Black Business Ownership and Lender Identity: The Effect of Racial Animus with Education and Income Controls

Dependent variable:				𝟙(Fintech)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	0.121***	0.280***	0.271***	0.235***	0.163**	0.170**	0.242***
	(0.002)	(0.074)	(0.075)	(0.077)	(0.075)	(0.074)	(0.074)
𝟙(Black-Owned) × Racial Animus		0.015***	0.013***	0.006***	0.016***	0.028***	0.015***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
𝟙(Black-Owned) × Share Black Pop. w/ Bachelor's		0.145***	0.140***	0.113***	0.121***	0.062***	0.093***
		(0.025)	(0.025)	(0.026)	(0.025)	(0.024)	(0.025)
𝟙(Black-Owned) × Med Black HH Income		-0.018**	-0.017**	-0.013*	-0.007	-0.007	-0.014*
		(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Racial Animus Measure		IAT (Implicit)	IAT (Explicit)	Stephens-Davidowitz	Nationscape	Segregation (Isolation)	Segregation (Dissimilarity)
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code 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

Note: This table repeats Table 6 Panel A on a subsample of counties that have ACS data, with additional controls for local education and income levels among the Black population. Local Black education is defined as the percent of the Black population with at least a bachelor's degree, and local Black income is defined as the median Black household income. The racial animus measures are as follows: columns 2-3 use the implicit and explicit score from the Implicit Association Test (IAT) aggregated to the county level; column 4 uses the number of racially charged searches in a designated media market (DMA); column 5 uses responses to the question on favorability toward Black people in the Nationscape survey aggregated to the congressional district 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 Table 4. Standard errors are clustered by zip code. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.18: Summary Statistics by Predicted Race

Panel A: Application Sample (Lendio)

	All	Asian-Owned	Black-Owned	Hispanic-Owned	White-Owned
Number of Lenders Sent					
All	1.561	1.623	1.495	1.568	1.562
Fintech	0.949	1.046	0.990	0.913	0.930
Conventional	0.612	0.577	0.505	0.655	0.631
Share of Lenders Sent					
Fintech & Conventional	16.4%	18.0%	16.0%	16.7%	16.1%
Fintech Only	56.7%	61.3%	63.1%	54.3%	55.1%
Conventional Only	26.9%	20.7%	20.8%	29.0%	28.8%
Observations	278,404	31,682	34,195	30,090	182,394

Panel B: 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 the Lendio applications-matched and credit and debit card revenue-matched samples. Panel A contains statistics about the data on PPP applications from the Lendio platform. The "conventional" category includes all non-fintech lenders. Panel B summarizes the credit and debit card revenue data in the Enigma card revenue-matched sample. We define firms as "struggling" if they had revenue in February 2020 but not in the month of approval.

Table A.19: 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)
Approval Week FE	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes	Yes
Zip Code 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:	$\mathbb{1}$(PPP Lender is) Checking Acct Bank		$\mathbb{1}$(Top-4 Bank)		$\mathbb{1}$(Large Bank)		$\mathbb{1}$(Small/Med Bank)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Asian-Owned)	-0.007	-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)
$\mathbb{1}$(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)
$\mathbb{1}$(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)
$\mathbb{1}$(Credit from Fintech)		-0.040***		-0.025***		-0.011***		-0.035***
		(0.004)		(0.003)		(0.002)		(0.003)
$\mathbb{1}$(Credit from Conv.)		0.011***		0.001		0.005**		-0.002
		(0.003)		(0.002)		(0.002)		(0.003)
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code 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 2, 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 8. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.20: 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)
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code 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)
Approval Week FE	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes
Zip Code 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 2. In Panel A, we add controls for firm revenue from credit and debit card transactions during and two months prior to the PPP loan approval month. The sample is restricted to firms 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 A.21: How Race Predicts Fintech with Card Revenue Controls within Approval Month

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)	0.024***	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)
Approval Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code 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 2, 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 A.20. Standard errors are clustered by borrower zipcode. ***,** ,* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.22: 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-4 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 A.4 Panel A, and thus has a smaller sample size. We also report the share of these loans originated by small banks, top banks, and fintechs.