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Lender Automation and Racial Disparities in Credit Access

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ABSTRACT

Process automation reduces racial disparities in credit access by 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), where private lenders faced no credit risk but decided which firms to serve. Black-owned firms obtained PPP loans primarily 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, preexisting banking relationships, firm performance, or fraud rates.

RESEARCHERS AND POLICY MAKERS IN THE United States 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 important questions about how their technologies—notably, algorithmic underwriting and process automation—might affect racial

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disparities in lending. Much of this literature focuses on the effects of algorithmic underwriting practices on racial disparities in credit access (Blattner, Nelson, and Spiess (2021), Bartlett et al. (2022), Fuster et al. (2022)). In this paper, we study the role of process automation 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 often goes hand-in-hand with online loan origination procedures, which 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 thus can mitigate racial discrimination—whether of the taste based or statistical variety—in lending. Using an array of novel data sets, 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 disentangling 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 a 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 Coronavirus Aid, Relief, and Economic Security (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 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 preexisting 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 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 a 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 business owners for 4.2 million PPP loans. Predicted race based on signals provided by name and location is particularly relevant in our context, since loan officers typically observe these characteristics but do not know borrowers' actual race. Our results are robust to using only the subsample of PPP borrowers with information on self-identified race.

To establish the effect of automation on racial disparities in small business lending, we use two approaches. First, we study the rates of lending to minority-owned businesses across lender types with different degrees of automation, where fintech firms have the most automated lending systems and small banks have the least automated systems. (We use data on 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 who automated their loan origination processes during the PPP period. Both sets of analyses show that lenders with more-automated loan processing systems were more likely to extend PPP loans to minority-owned firms. Our evidence suggests that this result is due in part to lenders with more automated systems making smaller loans and loans in higher minority areas, and in part to automated loan processing reducing the scope for human biases to lead to discrimination in lending. Data from a subset of PPP loan applications provide additional evidence that racial differences in loan approval rates at conventional lenders (but not at fintechs) contribute to the observed cross-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. Among fintech lenders with the most automated lending systems, 26.5% of their PPP loans were issued to Black-owned businesses. Among traditional banks, PPP loan shares to Black-owned businesses were increasing with bank size, ranging from 3.3% at small banks to 6.2% at the four largest 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 accounting for only 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 lender types are much more dramatic, and thus we focus here 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 might be more likely to serve borrowers in areas where the lenders have a physical presence, leaving fintech lenders to 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 40 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%. Including controls for firm characteristics reduces this difference to 12.1 percentage points. Similarly, Black-owned firms are unconditionally 31 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 49.8%), a gap that falls to 8.2 percentage points after controlling for firm characteristics. In addition to this cross-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 of automating on making a PPP loan to a Black-owned firm is 4.3 percentage points, which represents nearly a doubling of the pre-automation Black-owned share among the relevant lenders.

Overall, our 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 automation also reduces racial disparities in small business lending 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 United States, preference-based discrimination has particular ethical and regulatory implications. The PPP setting 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 the possibility 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 support the view that automation can 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. This is true both within lenders who automate their loan origination process over time, as well as 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. This in part reflects automated lenders being able to profitably make smaller loans that are particularly common for minority-owned businesses, and in part reflects automation reducing 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 the extent to which they have automated their loan origination processes, and hence in the extent to which human biases affect prioritization and approval decisions, they also differ on other characteristics that likely contribute to the observed cross-lender heterogeneity in lending to Black-owned firms. Thus, in the remainder of the paper, we explore whether the cross-lender patterns can be *fully* explained by such differences, including racial differences in firms' PPP application behaviors or preexisting 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 the degree to which these other factors contribute to the overall cross-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 cross-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 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 but not applications, we assess this possibility using data on PPP loan applications from the marketplace lending platform Lendio. These data contain information on approximately 280,000 completed PPP loan applications that 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 likelihood 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 racial disparities are even stronger when the application was routed to a small bank. Therefore, the least automated lenders appear most likely to reject PPP loan applications from Black-owned firms, relative to otherwise similar firms with firm owners of other races. This finding shows that lower rates of originating PPP loan applications from Black-owned firms at banks (but not at fintechs) contributes to the observed cross-lender disparities in lending to Black-owned firms. This finding also highlights important real effects of automation: Automation impacts not only the identity of the final PPP lender, but also the ability of Black-owned firms to obtain any PPP loan 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 using 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 part 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 72.6% of firms that obtained 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 nonrelationship fintech lender, and much less likely to obtain it from a nonrelationship small bank.

Finally, we examine 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 may still have prioritized firms that appeared to be more profitable future customers. We find, however, that the observed racial disparities are unaffected by controls for monthly credit and debit card revenues or bank statement cash flows. This result 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. We find no evidence that differential fraud rates drive the results.

Several contemporaneous papers offer results consistent with ours. Erel and Liebersohn (2020) find 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 show 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 (2022) use rich data on restaurants to study PPP take-up. They show that minority-owned businesses are less likely to get a PPP loan 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 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, Dobbie, and Yang (2018), Bertrand and Mullainathan (2004), Knowles, Persico, and Todd (2001), Anwar

[1] Other researchers have examined whether firm size or preexisting banking relationships can explain access to PPP loans (Humphries, Neilson, and Ulyssea (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. (2020), Bartik et al. (2020), Fairlie (2020), Kim, Parker, and Schoar (2020), Hubbard and Strain (2020), Faulkender, Jackman, and Miran (2020), Granja et al. (2020), Autor et al. (2020), Bartlett and Morse (2020)).

and Fang (2006), Charles and Guryan (2008), Price and Wolfers (2010)), including racial disparities in access to financial services (see, for example, Tootell (1996), Bayer, Ferreira, and Ross (2018), Bhutta and Hizmo (2021), Ambrose, Conklin, and Lopez (2020), Giacoletti, Heimer, and Yu (2021), Begley and Purnanandam (2021), Blattner and Nelson (2021)). Most directly relevant is work on the role of race in small business lending (Blanchflower, Levine, and Zimmerman (2003), Robb and Robinson (2018), Fairlie and Robb (2007), Asiedu, Freeman, and Nti-Addae (2012), Bellucci, Borisov, and Zazzaro (2013), Fairlie, Robb, and Robinson (2020)).

More broadly, our findings contribute 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, Johnson, and Stulz (2021)). Most closely related to this paper is a literature that explores the role of fintech lenders in extending credit to traditionally underserved minorities (Buchak et al. (2018), Tang (2019), Fuster et al. (2019), Balyuk, Berger, and Hackney (2020), Berg et al. (2020), D'Acunto et al. (2022), Bartlett et al. (2022), Atkins, Cook, and Seamans (2022)). 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 help reduce racial disparities in credit outcomes.

I. The PPP: Setting and Data

The PPP was established as part of the 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 nonbinding "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 5,310 lenders and totaling $799 billion, had been approved.

PPP Terms: PPP loans were government-guaranteed and uncollateralized. The loan amount was fixed at 2.5 times a firm's 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 for loans of more than $350,000 and less than $2,000,000; and
- 1% of the loan amount for loans of at least $2,000,000.

As a result of their preexisting 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 preapproved 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 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] 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).

(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 attention to the first few weeks of PPP loan approvals—legal experts indicated that lenders faced minimal enforcement risk.[3] This benefited smaller banks, which typically have less robust and less automated compliance infrastructure[4] (Duren (2020)).

Since minimal lender risk in the PPP context is important for our conclusions, we summarize the lender's risks via a series of questions and answers. First, what happens if the borrower does not 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.

A. 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. Hereafter, we refer to the loan originator as the "PPP lender." To construct our data set, we retain only a firm's first loan, so that each firm appears once. Specifically, we begin with a raw data set from the SBA, which has 11.8 million loan observations. Of these, 2.9 million are

[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 under the CARES Act, "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"

tagged as second draws (where a firm legally obtained a second PPP loan). After dropping these observations, we are left with 8.8 million first PPP loans.

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. Our results are very similar, however, when we use the full time period and when we include second-draw loans.

B. Lender Classification

In some of our analyses, we explore 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:

(i) Top 4 banks by assets (JP Morgan Chase, Bank of America, Wells Fargo, and Citibank);
(ii) Large banks: banks with more than $100 billion in assets, excluding the top 4 banks;
(iii) Medium-sized banks: banks with more than $2.2 billion in assets (but below $100 billion);
(iv) Small banks: banks with less than $2.2 billion in assets;[5]
(v) Credit unions: based on the lender name (i.e., "credit union" or "CU" at the end of the name);
(vi) CDFIs and nonprofits;
(vii) Minority Depository Institutions (MDIs): as classified by the FDIC;
(viii) 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 who 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] Internet Appendix Table IA.I lists all lenders classified as "fintech." In some cases, the originator listed in the table made loans primarily through fintech partners. For example, all of PayPal's fintech loans were originated by WebBank, and Square's loans by Celtic Bank. The only fintech lender with a branch is Cross River. However, Cross River originated an overwhelming quantity of loans for fintech partners such as Kabbage, 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. The Internet Appendix is available in the online version of the article on *The Journal of Finance* website.

Table I 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 75% of PPP loans, with non–top 4 banks responsible for 59% of all loans. Fintech lenders originated 17.4% of all PPP loans, while credit unions originated about 4%, and CDFIs and MDIs between 1% and 2%. Fintech and other nonbank lenders made substantially smaller loans. The average (median) PPP loan amount for fintech lenders is $31,228 ($15,338) compared to, for example, $88,083 ($20,833) for small banks.

Cross-Lender Variation in Automation: The degree of process automation differs widely across the different types of lenders. At one end of the spectrum are fintech firms, which achieve substantial cost savings by fully automating their loan origination processes. 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

[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 of 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."*

Table I

Summary Statistics by Lender Type

This table reports summary statistics for 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 analyses are drawn from subsamples of the data included in Panel B. Panel C reports statistics for banking and credit relationships as well as financial performance for 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 the PPP loan. The remaining variables are derived from transactions on the borrowers' most recent monthly bank statement. Internet Appendix Table IA.II repeats Panels B and C for the subset without predicted race.

Panel A: All PPP loans

				PPP Loan Amount ($)			
	Number Lenders	Number Loans	Total Amt ($ bn)	Mean	P10	P50	P90
All	5,310	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	18	898,175	108.8	121,127	6,000	28,133	230,895
Medium Banks	420	2,135,084	271.1	126,977	6,095	30,500	266,410
Small Banks	3,548	2,526,637	191.9	75,950	4,165	20,832	153,000
Credit Union	958	378,673	15.7	41,479	3,602	15,882	82,422
CDFI/Nonprofit	221	1,516,834	34.4	22,711	4,400	20,000	20,833
Minority Dep Inst	115	288,072	16.5	57,363	3,575	17,755	105,600
Fintech	29	2,766,912	65.6	23,726	3,083	17,208	29,166

(*Continued*)

Table I—*Continued*

Panel B: Analysis sample

	Number Lenders	Number Loans	Total Amt ($ bn)	PPP Loan Amount ($) Mean	P10	P50	P90	Share Black Borr	Share White Borr
All	5,266	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	18	393,884	57.7	146,505	6,250	32,100	279,297	5.3%	81.4%
Medium Banks	420	1,017,781	145.2	142,616	6,200	33,600	295,500	4.1%	84.0%
Small Banks	3,538	1,064,306	93.7	88,083	4,552	20,833	175,848	3.3%	88.9%
Credit Union	938	173,368	7.9	45,412	3,550	16,000	89,567	9.7%	78.1%
CDFI/Nonprofit	209	82,276	5.9	71,564	3,904	20,800	145,833	10.6%	74.4%
Minority Dep Inst	114	61,653	5.8	93,838	4,600	23,234	180,800	4.0%	27.2%
Fintech	28	726,884	22.7	31,228	2,853	15,338	54,465	26.5%	49.2%

(*Continued*)

Table I—*Continued*

Panel C: Bank and credit relationships sample (Ocrolus)

	N	Mean Loan Amount	SME Has Checking Acct with PPP Lender	Credit With Any: Fintech	Non-Fintech	Monthly Net Cash Inflow ($) Mean	P50	Share Black Borr	Share White Borr
All	168,360	80,897	27.4%	14.2%	80.0%	9,016	1,332	15.3%	63.5%
Top 4	29,709	72,738	67.2%	15.6%	87.3%	11,939	2,773	8.4%	63.6%
Large Banks	15,179	104,023	48.8%	14.7%	82.3%	12,226	2,491	8.1%	74.6%
Medium Banks	28,430	133,374	38.4%	14.5%	75.5%	9,371	1,482	5.9%	78.3%
Small Banks	22,818	118,334	23.3%	14.5%	75.5%	7,730	1,248	6.1%	79.9%
Credit Union	5,644	56,194	34.5%	13.0%	72.0%	6,794	825	14.2%	69.5%
CDFI/Nonprofit	3,046	66,732	8.4%	13.6%	79.1%	8,141	1,178	17.8%	61.4%
Minority Dep Inst	2,479	112,982	14.3%	13.3%	75.2%	3,302	1,069	5.7%	28.4%
Fintech	61,055	42,379	0.0%	13.3%	80.7%	7,592	932	28.7%	48.6%

IT spending for the years 2017 to 2019, provided by Spiceworks Ziff Davis (SWZD).[9] We observe spending data from 108,099 branches of 3,440 unique conventional PPP lenders. Following He et al. (2021), we use software spending to proxy for investment in automation, and construct average annual branch-level software spending between 2017 and 2019.[10] Panel A of Internet Appendix Figure IA.1 shows the distribution of branch-level software spending for different bank types (Internet Appendix Table IA.VII 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 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, in contrast to substantial growth at large banks.

C. 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 construct a signal of race and ethnicity for a larger set of PPP borrowers, we build on a well-established literature and 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 nonemployer firms, we rely on the fact 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 firm's address, industry, and employer status. Based on these data, we use a machine

[9] These data, formerly known as the Harte Hanks Market Intelligence Computer Intelligence Technology database, are sold as market intelligence to technology firms and have been used by Forman, Goldfarb, and Greenstein (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.

[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 the headquarters level.

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

learning approach to estimate the conditional probability of a business owner being Asian, Black, Hispanic, or White.

Our process involves two steps. In the first step, 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 Section I.A of the Internet Appendix 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 800,000 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 as having the race with the largest probability across the set of racial groups $\mathcal{R}$.[12]

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." To assess the out-of-sample quality of the prediction, we randomly set aside a "hold-out" subsample of borrowers who self-identify their race but whom we exclude from the training of the random forest model. Table IA.III shows that in the hold-out sample, 84% of those business owners who we predict to be Black self-identified as Black.

We show below that our main results on the effects of both cross-lender and within-lender variation in automation are robust to using the subsample of borrowers for whom the SBA data include information on self-identified race. However, our signal of predicted race is likely to be more relevant in our setting because loan officers typically 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 Mul-

[12] The probability distributions for each race as predicted by the algorithm are summarized in Internet Appendix Table IA.III and Figure IA.2. For example, among people predicted to be Black, the mean the probability 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 for which this probability is larger than 90%, or when we use this probability directly instead of a race dummy.

lainathan (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 I and Panel A of Internet Appendix Table IA.IV 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 IA.V). For example, the average PPP loan amount is $93,784 in the full sample and $93,666 in the analysis sample. Thus, 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.

II. 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 increase lending to minority-owned firms through several mechanisms:

(i) 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 II).

(ii) 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)).

(iii) 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.

[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, Internet Appendix Table IA.VI shows that 2.8% 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.

Table II

Summary Statistics by Predicted Race

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.

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%	18.1%	11.5%	17.1%	27.3%
Small Banks	25.4%	12.4%	9.8%	11.7%	30.2%
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	1.5%	8.0%	0.7%	4.0%	0.5%
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

(*Continued*)

Table II—*Continued*

Panel B: Bank and credit relationships sample (Ocrolus)

	All	Asian-Owned	Black-Owned	Hispanic-Owned	White-Owned
Banking Relationships					
Share Checking Account from Top 4 Banks	47.8%	57.5%	47.1%	61.9%	44.1%
Share Checking Account from Large Banks	15.8%	13.6%	19.1%	11.6%	16.0%
Share Checking Account from Small/Medium-Sized Banks	27.5%	20.3%	16.5%	19.9%	32.7%
Share Checking Account 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

There are also forces through which process automation may reduce 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, 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.

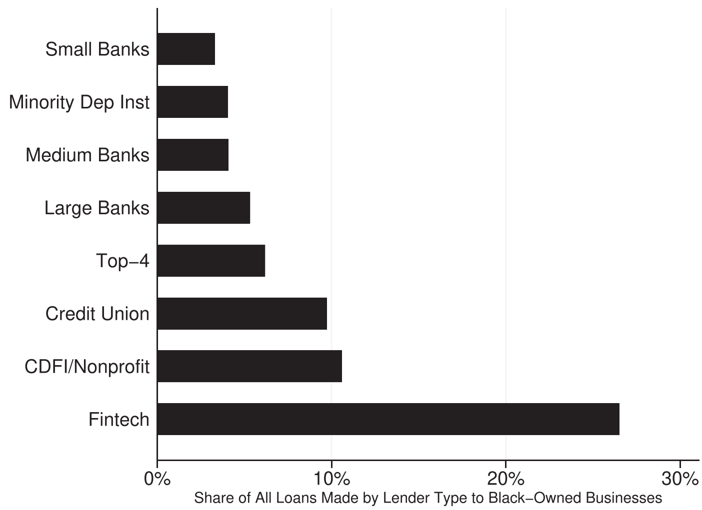
A. *Cross-Lender Variation*

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 cross-lender variation in extending PPP loans to minority-owned business and 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 I). 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 issued 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 II). Internet Appendix Table IA.I shows that while there is some variation across fintech lenders in the share of PPP loans to Black-owned firms, this variation is not driven by a few lenders.

We present the corresponding figures for other racial and ethnic groups as well as by gender in Internet Appendix Figures IA.4 and IA.5. Lending to Black-owned firms exhibits the most striking variation 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, Matvos, and Seru (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.

Panel A. Share of PPP Loans to Black-Owned Businesses by Lender Type



Panel B. Share of Lender Type among PPP Loans to Black-Owned Businesses

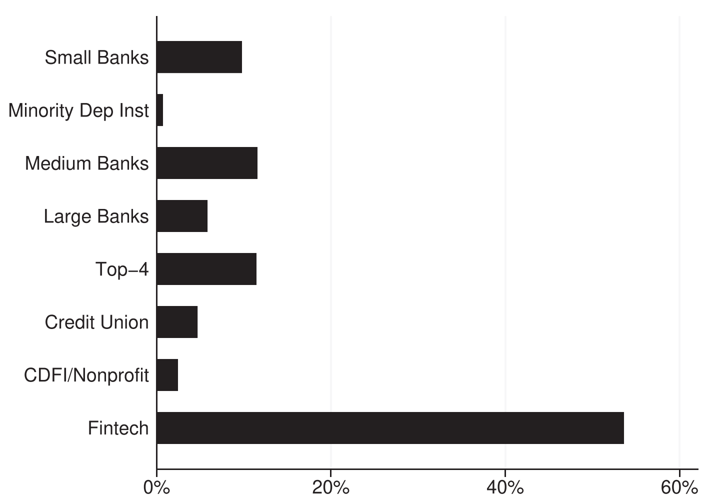


Figure 1. Black-owned business PPP lending by lender type. Panel A shows, for each lender type, the share of PPP loans that went to Black-owned businesses (P(Black-owned|Originating Lender Type)). Panel B shows the share of all PPP loans to Black-owned businesses made by each lender type (P(Originating Lender Type|Black-owned)).

In Panel B of Figure IA.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.

B. 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 may differ along characteristics other than automation that can affect both the propensity of minority-owned firms to apply and the propensity of lenders 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.

B.1. 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 can 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 faces 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

[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.

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

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

	Automating Banks $N = 20$			Nonautomating Banks $N = 3{,}941$		
	Mean	P50	*SD*	Mean	P50	*SD*
Number of Loans	3,748	1,250	6,062	511	187	1,634
Assets (Million $)	8,673	1,235	15,078	1,243	269	4,753
Loan Amount ($)	131,297	129,011	61,355	77,820	59,044	73,927
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%	5.8%
Asian-Owned Share After Automation	7.3%	5.4%	10.4%	3.5%	1.8%	5.8%
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%	7.4%
Hispanic-Owned Share After Automation	6.4%	5.5%	5.9%	3.0%	1.1%	7.4%
White-Owned Share Before Automation	85.0%	87.7%	13.4%	90.8%	94.3%	11.5%
White-Owned Share After Automation	74.4%	72.6%	21.5%	90.8%	94.3%	11.5%

loans in our analysis sample, or 3.6% of all PPP loans originated by small and medium-sized banks. Table III presents summary statistics for the automating banks and the control group of otherwise similar nonautomating banks. Among automating banks, about 30% of their PPP loans occur after automation. Automating banks are somewhat larger than banks in the control group.

B.2. The Effect of Automation

Table III 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-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:

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

where $\mathbb{1}(\text{BlackOwned}_{ibt})$ 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, nonautomating 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 cross-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 who self-report race (Figure IA.8). Second, when we estimate equation (1) at the weekly level for banks that originate loans over the six weeks on both sides of the automation date, we find no pretrends 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 (Figure IA.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 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 cross-lender differences in lending to minority-owned firms.

III. 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 by 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

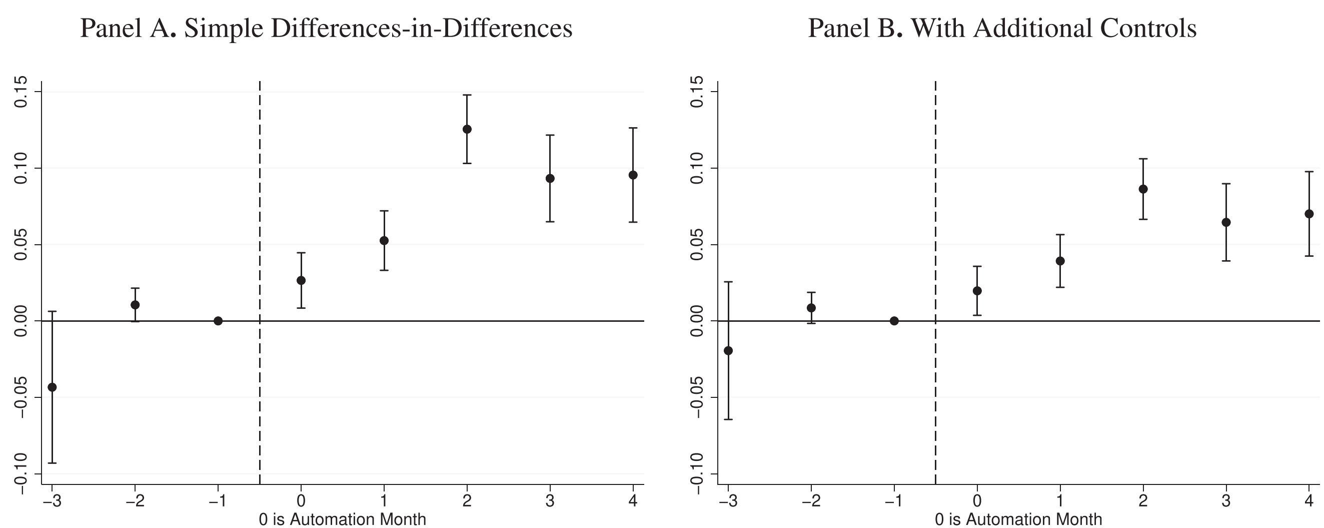


Figure 2. Share of loans to Black-owned businesses before and after small-bank automation. This figure reports dynamic differences-in-differences estimates at the monthly level (see equation (1)). Period 0 following the dashed vertical line corresponds to the automation month. Panel A includes fixed effects for the bank and week of loan approval. Panel B adds the vector of controls included in Table V, Panel A, column (2). We do not include more than three months before automation because the automation dates (in late Spring 2020 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 gray bars represent 95% confidence intervals.

Black-owned businesses, we use the regression framework in equation (2):

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

The dependent variable, $LenderType_i$, is an indicator for whether PPP borrower i's loan comes 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 $LenderType_i = Fintech_i$, 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. The vector $\mathbf{X}_i$ represents a vector of control variables.

A. Lending to Black-Owned Firms by Fintech Lenders

Panel A of Table IV reports results from regression (2) with $LenderType_i = Fintech_i$. Column (1) shows that, consistent with Section II.A, 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 Figure IA.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 Table IA.VIII). 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 differences among loans originated at the same time. Those differences are unlikely to be confounded by timing factors unrelated to automation, and present a lower bound on the total variation that is determined by lender characteristics. Column (2) of Table IV 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 II). Under 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 view, Table I 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 IV, Panel A, we add fixed effects for each percentile of the loan size distribution. Controlling for loan amount explains some of the variation, consistent with the ability to

Table IV

Business Owner Race and PPP Lender Type

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) and (2)), a large bank (columns (3) and (4)), and a small/medium-sized bank (columns (5) and (6)). Panel C is estimated on the sample of PPP loans matched to 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 zip code (or county, if there is no zip code 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 the SBA. Industry FE are 104 indicators for NAICS three-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. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Fintech PPP loan

	$\mathbb{1}$(Fintech)						
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}$(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

	$\mathbb{1}$(Top 4 Bank)		$\mathbb{1}$(Large Bank)		$\mathbb{1}$(Small/Med Bank)	
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Black-Owned)	−0.049***	−0.008***	−0.039***	−0.025***	−0.311***	−0.082***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(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	0.498	0.498
R^2	0.001	0.317	0.001	0.131	0.030	0.396
Observations	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623	4,183,623

(*Continued*)

Table IV—*Continued*

Panel C: Branch software spending and PPP loans to Black-owned businesses

	Log(Branch Software Spending)					
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(Black-owned)	0.071***	0.032***	0.025***	0.025***	0.015***	0.006**
	(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	10.799	10.799	10.799	10.799	10.799	10.799
Observations	2,928,221	2,928,221	2,928,221	2,928,221	2,928,221	2,928,221

serve smaller loans 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 turn to 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 IV, Panel A, we add zipcode fixed 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 technology and automatically processing diverse documents, including handwritten payroll slips, creating an advantage in sectors with less formal accounting systems, which have higher shares

[15] In Table IA.IX, we verify that all businesses located in areas with high minority ownership—even businesses in areas that are owned by White individuals—were somewhat more likely to obtain their PPP loans through fintech lenders.

of Black-owned firms.[16] We include industry fixed effects in column (5) of Table IV, Panel A, to control for such industry-specific differences.[17] Even within an 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) versus column (2) of Table IV, Panel A). This finding suggests that fintech lenders are indeed more likely to lend to Black-owned firms 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 loans from a fintech lender than otherwise identical businesses owned by individuals of a different race or ethnicity.

B. 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 large banks' processes are not nearly as automated as those of fintech lenders. Section II.A highlights 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 IV, 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. To do so, we replace $LenderType_i$ in equation (2) with an indicator for obtaining a 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. In contrast, the majority of the 12.1 percentage point fintech differential in column (7) of Panel A of Table IV is accounted for by lower rates of PPP lending to Black-owned firms by small and medium-sized banks—those banks with the lowest degree of automation in the loan origination process.[18] These small and medium-sized banks were instead

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

[17] Borrower industry is captured with NAICS three-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 II, Panel A, shows that the industry distribution differs 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 depicts the conditional cross-lender patterns by comparing all types of lending institutions simultaneously. Here, we show the degree to which the lender types were statistically

disproportionately likely to lend to White-owned firms (see Table IA.X). Section II of the Internet Appendix presents robustness tests of these cross-lender findings. For example, we show that the results are similar in the smaller and potentially selected sample of individuals who self-reported race. Other tests document persistent effects across periods within the PPP as well as when separately considering, for example, employer versus nonemployer firms.

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 IV, we present results from equation (2) using the log of branch-level software spending between 2017 to 2019 as the dependent variable. The results are consistent with the cross-lender-type analysis. Unconditionally, Black-owned firms obtain their PPP loans from branches with about 7.1% higher spending on software in 2017 to 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 part of the reason why automation caused banks to increase their loan shares to Black-owned firms during the PPP period is that it allowed banks to make smaller loans (see Section II.B). 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 identify how much of the treatment effect of automation can be explained by

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 5 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 so, we first construct branch-level software spending at the zip code level for each bank, excluding the bank headquarters site. We then match PPP borrowers to software spending at the bank zip code level. For example, a PPP borrower in zip code 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 zip code, 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. 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) similarly notes 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*

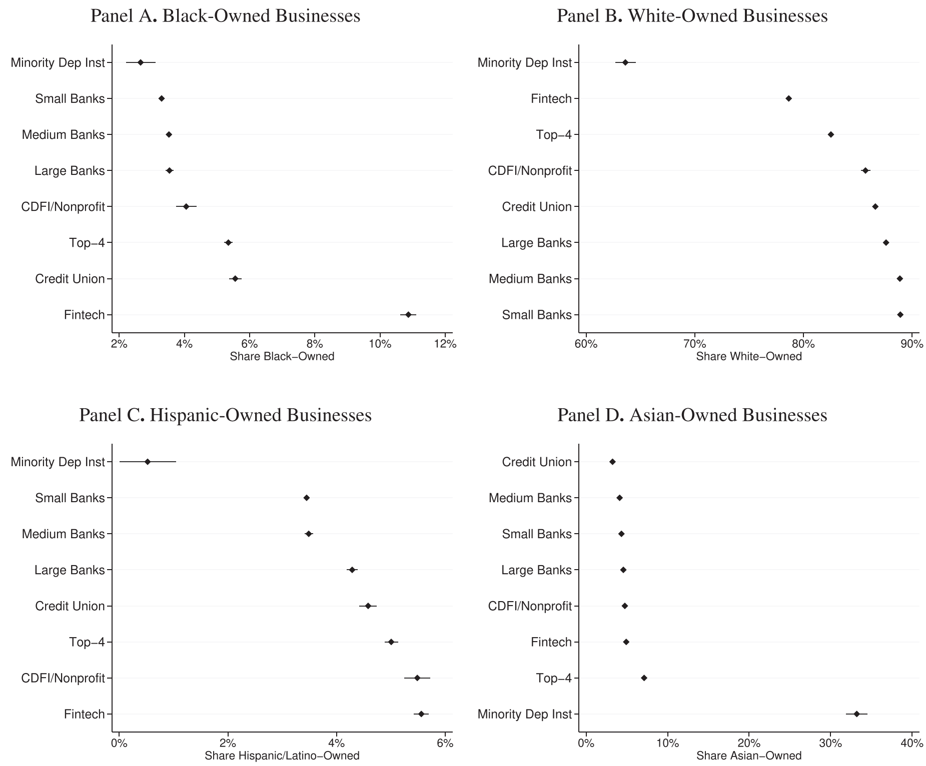


Figure 3. Conditional share of PPP loans to each race by institution type. This figure shows shares of PPP loans made to Black-owned businesses by originating lender type. Each graph presents β coefficients from variations of the following regression: Black-owned$_i$ = βLender Type$_i + \gamma \mathbf{X}_i + \epsilon_i$, where $\mathbf{X}_i$ is a vector of fixed effects for borrower zip code, loan amount percentile (in 100 bins), approval week, three-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 interpretation of coefficients.

compositional changes in loan characteristics on nonrace 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

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."

white-label fintech) as of week t, α_b is a bank fixed effect that controls for any baseline differences in lending to Black-owned firms, α_t is a fixed effect for the week of loan approval that removes any general time trends in the share of loans by small banks to Black-owned firms, and $\mathbf{X}_i$ 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 V. The baseline differences-in-differences model controlling only 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 6 percentage points after automation, relative to a preautomation share of 4.4%. In column (2), we add the same set of controls as in Table IV, 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 V, 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 nonautomating banks. Following 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.

IV. Mechanisms: The Role of Discrimination

Above we documented that the automation of lending processes is associated with a higher probability of lending to Black-owned firms. This is true both across 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, and 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- 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 the applicant's name, which we have shown

[21] In columns (3) to (5) of Table V, 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.

Table V

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

This table reports estimates of equation (3), estimated on the sample of PPP loans extended by small and medium banks. Columns (1) and (2) of Panel A show the effect of automation on the probability that a loan is extended to a Black-owned business. Columns (3) to (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 VI), 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 IV. Standard errors are clustered by zip code. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Bank automation on loan share by race and ethnicity

	𝟙(Black-Owned)		𝟙(Owned by:)		
			Hispanic	Asian	White
Dependent Variable:	(1)	(2)	(3)	(4)	(5)
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	0.044	0.055	0.865
Observations	2,090,197	2,090,197	2,090,197	2,090,197	2,090,197

(*Continued*)

Table V—*Continued*

Panel B: Bank automation on loan share by race and ethnicity and racial animus

	$\mathbb{1}$(Black-Owned)					
Dependent Variable:	(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) × Racial Animus	0.009***	0.009***	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	2,090,197	2,090,197	2,090,197	2,090,197	2,090,197	2,090,197

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 difference should be larger in regions with higher racial animus. We next explore this hypothesis by studying the interaction between the degree of automation and 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 (2014). The second measure follows Bursztyn et al. (2021) and is based on how favorably White respondents rate Black Americans as a group in the Nationscape survey (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 toward Black Americans (Xu, Nosek, and Greenwald (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 measures the probability of a Black resident sharing the same census tract with another Black resident.

Section I.C of the Internet Appendix 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, Figure IA.14 shows that the places where racial animus is high differ substantially across our measures, indicating that they offer somewhat independent signals of animus.

Cross-Lender Racial Disparities by Racial Animus: Table VI 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 IV, Panel A. In columns (2) to (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.

[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, Akinola, and Chugh (2012), Bartoš et al. (2016)).

Table VI

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

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 IV, Panel A, column (7). The racial animus measures are as follows: columns (2) to (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; and columns (6) to (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 IV. Standard errors are clustered by zip code. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fintech PPP loans as dependent variable

	𝟙(Fintech)						
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	0.121***	0.120***	0.121***	0.124***	0.121***	0.117***	0.107***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
𝟙(Black-Owned) × Racial Animus		0.013***	0.011***	0.004**	0.014***	0.016***	0.029***
		(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

	𝟙(Non-Top 4 Bank)						
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	−0.107***	−0.105***	−0.107***	−0.108***	−0.107***	−0.104***	−0.094***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
𝟙(Black-Owned) × Racial Animus		−0.022***	−0.014***	−0.013***	−0.012***	−0.012***	−0.028***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dep Var Mean	0.592	0.592	0.592	0.592	0.592	0.592	0.592

(*Continued*)

Table VI—*Continued*

Panel C: Top 4 bank PPP loans as dependent variable

	𝟙(Top 4)						
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
𝟙(Black-Owned)	−0.008***	−0.009***	−0.008***	−0.009***	−0.008***	−0.008***	−0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
𝟙(Black-Owned) × 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 (Dissimilarity)	Segregation (Isolation)
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

In Panel A of Table VI, 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 probability of a fintech loan of 17.4%, a one-standard-deviation increase in racial animus is associated with a 2.3% to 16.7% 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 show 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 2.2 percentage point decrease in the likelihood 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 systematically vary with the degree of racial animus.

In Table IA.XVII, we show that our measures of racial animus in these specifications do not simply 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 somewhat stronger with these additional interactions.

The Effect of Bank Automation by Racial Animus: In Panel B of Table V, 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 insignificant 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. Table IA.XII, 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 PPP lending to Black-owned firms is by reducing the effect of preference-based discrimination.

V. Mechanisms: Loan Applications and Rejections

Our analysis so far studies racial differences in PPP lender identity among firms that ultimately received PPP loans. Our interpretation of the observed racial differences 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, because Black-owned firms are generally smaller and thus 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 reflect Black-owned firms applying more frequently to fintech lenders (as documented in other settings by Barkley and Schweitzer (2020), Barkley and Schweitzer (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 next show that differential application behavior also cannot fully explain our cross-bank findings (though our data do not allow us to rule out that they contribute to the differences).[24]

A. Lendio Loan Application Data

We obtain data on PPP applications to the marketplace platform Lendio through November 2020. 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 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

[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 anticipate discriminating treatment, the main thrust of our findings remains unchanged. Indeed, substitution away from lenders who discriminate may partially explain demand for fintech products more generally.

over the application routing. These data, therefore, permit us to largely hold fixed firms' application behavior.

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 (Table IA.XVIII). Among the firms whose PPP applications were forwarded by Lendio to at least one lender, just over 60% ultimately received 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 25% 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 on the Lendio sample and its demographic breakdown are summarized in Panel C of Table IA.IV. 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.

B. Analysis of Lendio Loan Applications

In Table VII, we analyze PPP loan outcomes for applicants through the Lendio platform. We consider two outcomes: (i) whether the firm ultimately receives a 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 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 VII, we restrict the sample to PPP applications that were sent only to fintech lenders (recall that, conditional on loan characteristics, which lenders an application gets forwarded to is random). 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 differences 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

Table VII

Lending to Black-Owned Firms Conditional on Applications

This table reports estimates of a modified version of equation (2) within the sample of PPP loan application to Lendio. Columns (1) and (2) include the full sample, columns (3) and (4) restrict attention to the subsample of applications that Lendio quasi-randomly forwarded only to fintech lenders, columns (5) and (6) restrict attention to the subsample of loans that were forwarded only to conventional lenders, and columns (7) and (8) restrict attention 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 who 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 (through a Lendio lender or an alternative lender). We include fixed effects for each combination of lenders who the application was routed to. Other controls are as described in Table IV, with the exception that we include application week fixed effects instead of origination week fixed effects. Standard errors are clustered by zip code. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Sent to Lenders:	Any		Only Fintech		Only Conventional		Only Small Banks	
Dependent Variable:	𝟙(PPP Loan from Lendio Lender) (1)	𝟙(No PPP Loan) (2)	𝟙(PPP Loan from Lendio Lender) (3)	𝟙(No PPP Loan) (4)	𝟙(PPP Loan from Lendio Lender) (5)	𝟙(No PPP Loan) (6)	𝟙(PPP Loan from Lendio Lender) (7)	𝟙(No PPP Loan) (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

not selected on race, some of these firms subsequently applied to conventional lenders where they would face the same disparities described in Section IV.

In columns (5) and (6) of Table VII, 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 a 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 of higher rejection rates 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 systems on average. Consistent with our prior findings, racial differences 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 cross-lender differences (in addition to not explaining our within-lender findings). Instead, differences 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 a PPP loan at all, in addition to being less likely to get a PPP loan from that lender. There is no comparable racial disparity among firms whose applications are assigned to be processed by fintech lenders. This finding indicates that automation not only affects *which lender* Black-owned firms get their PPP loan from, but also whether they obtain a PPP loan *at all*. Thus, whatever the determinants of the racial disparities identified in this paper, they have important real effects.

VI. 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 preexisting 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.

A. Bank Statement Data

We employ 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 168,000 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 I shows that the bank statement sample and the full analysis sample are broadly similar along 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 result reflects the fact 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 80.0% had a credit relationship with a traditional bank (Table II, 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 I, 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 II shows that the mean net monthly cash inflow across all firms is \$9,016, while it is \$6,332 among Black-owned businesses.

B. 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 I shows that 27.4% 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 48.8%, and for medium and small banks it is 38.4% and 23.3%, 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 VIII 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 IV, 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 VIII, we find that, as in the full sample, Black-owned firms in the Ocrolus matched sample have no differential chance of a top 4 bank 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 data set 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 IX, 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 IX, 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 IX, Panels B and C).[25]

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

[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, the 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)).

Table VIII

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

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) and (2)), a large bank (columns(3) and (4)), or a small/medium-sized bank (columns (5) and (6)). We report coefficients on indicators for whether the borrower has previous credit relationships with fintech and nonfintech 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 IV. Standard errors are clustered by borrower zip code. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fintech PPP loan

	𝟙(Fintech)			
Dependent Variable:	(1)	(2)	(3)	(4)
𝟙(Black-Owned)	0.055***	0.055***	0.056***	0.055***
	(0.004)	(0.004)	(0.004)	(0.004)
𝟙(Credit from Fintech)			0.075***	0.078***
			(0.003)	(0.003)
𝟙(Credit from Conv.)			−0.012***	−0.011***
			(0.003)	(0.003)
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

(*Continued*)

Table VIII—*Continued*

Panel B: Bank PPP loan

	𝟙(Top 4 Bank)		𝟙(Large Bank)		𝟙(Small/Med Bank)	
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(Black-Owned)	0.005	−0.000	−0.017***	−0.019***	−0.047***	−0.037***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)
𝟙(Credit from Fintech)		−0.025***		−0.011***		−0.035***
		(0.003)		(0.002)		(0.003)
𝟙(Credit from Conv.)		0.001		0.005**		0.001
		(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	0.304	0.304
Observations	168,360	168,360	168,360	168,360	168,360	168,360

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 difference in this sample is largest among new clients at small banks—those banks with the least-automated application systems—with no evidence of substantial disparate treatment at top 4 banks.

We next explore whether prior credit relationships explain PPP lending patterns. In column (3) of Table VIII, 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 nonfintech lender reduces the likelihood of getting a fintech PPP loan and increases the probability of a nonfintech PPP loan. The preferential treatment of firms with prior credit relationships, however, does not account for the disproportionate

Table IX

Black Business Ownership and PPP Lender Type by Checking Account Bank Type

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 VIII. Standard errors are clustered by borrower zip code. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

			Banks:		
Dep Var:	𝟙(Lender is Bank) (1)	𝟙(Fintech) (2)	𝟙(Top 4) (3)	𝟙(Large) (4)	𝟙(Small/Medium) (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	0.188
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***	−0.041***
	(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	0.216

(*Continued*)

Table IX—*Continued*

Panel C: Sample of borrowers with checking accounts at small/medium-sized banks					
𝟙(Black-Owned)	−0.015	0.056***	−0.001	−0.008	−0.044***
	(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	0.591
Panel D: Sample of borrowers with fintech credit relationship					
𝟙(Black-Owned)	0.019	0.032**	0.016	−0.009	−0.040***
	(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	0.311
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

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 nonfintech lenders (Table VIII, Panel A, column (3)).

In Section V, 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 explored a specific such mechanism, 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 further test this hypothesis, we condition on firms in the bank statement–matched data that we observe having a preexisting credit relationship with fintech firms. Within this sample of firms, all of which show 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 toward fintech lenders (Panel D of Table IX). This finding implies that the main results are unlikely to be driven by higher fintech affinity among Black-owned firms.

VII. 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 Section II of the Internet Appendix, we consider two final mechanisms that may contribute to the observed cross-bank effects (although 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 this concern, we obtain data from Enigma, which observes 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 consists of firms that are on average larger and more sophisticated, Black-owned firms are still 16% 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 firm performance do not explain the results.

A final possibility is that the cross-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. Section II of the Internet Appendix presents a variety of evidence suggesting that this hypothesis is unlikely to explain our findings.

VIII. 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 who originated 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. What explains these observations, 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 explain these patterns. First, we find that racial differences in loan shares across lenders align with differences in automation rates, with the most automated lenders (fintechs) issuing the largest share of loans to Black-owned firms, while the least automated lenders (small banks) contributed 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 allowed fintechs to make smaller loans. Since loan size under PPP was tied to payroll and Black-owned firms tend to be smaller, this disproportionately 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 receive their PPP loans from a fintech lender. Moreover, we show that differential preexisting 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 explain lower rates of lending to Black-owned businesses among smaller conventional lenders. Since many of the variables we condition on partially reflect historical discrimination patterns (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.

Our results relate to the 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 the 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 potentially 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, reducing the scope for taste-based discrimination.

The PPP setting has many advantages to help shed light on 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 generalize 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, 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 not to process a loan application from a Black-owned firm could typically 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 Figures IA.6 and IA.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 racial disparities caused by automation to be larger in a normal lending market in which small banks do more of their business in person (Arnold, Dobbie, and Yang (2018), Knowles, Persico, and Todd (2001), Price and Wolfers (2010)). Better understanding the magnitudes of racial disparities across other lending markets is thus an important avenue for future research.

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Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.