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Applications or Approvals: What Drives Racial Disparities in the Paycheck Protection Program?

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Abstract

We use the 2020 Small Business Credit Survey to study the sources of racial disparities in use of the Paycheck Protection Program (PPP). Black-owned firms are 8.9 percentage points less likely than observably similar white-owned firms to receive PPP loans. About 55% of this take-up disparity is attributable to a disparity in application propensity, while the remainder is attributable to a disparity in approval rates. The finding in prior research that Black-owned PPP recipients are less likely than white-owned recipients to borrow from banks and more likely to borrow from fintech lenders is driven entirely by application behavior. Conditional on applying for a PPP loan, Black-owned firms are 9.9 percentage points less likely than white-owned firms to apply to banks and 7.8 percentage points more likely to apply to fintechs. However, they face similar average approval disparities at banks (7.4 percentage points) and fintechs (8.4 percentage points). Sorting by Black-owned firms away from banks and toward fintechs is significantly stronger in more racially biased counties, and the bank approval disparity is also larger in more racially biased counties. Neither differences in PPP demand nor differences in eligibility rates are able to explain any of our findings. Racial disparities in program awareness and in the burden of application requirements (e.g., submitting all required documentation) both appear to be important drivers of application disparities, and the latter also helps to explain both bank and fintech approval disparities.

Key words: discrimination, racial disparities, Paycheck Protection Program, bank lending, fintech lending, administrative burden

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The Internet Appendix is available at
https://www.dropbox.com/s/4vl719fl4947p45/PPPApplicationsApprovalsInternetAppendix.pdf?dl=0.

1 Introduction

The $800 billion Paycheck Protection Program (PPP), authorized by Congress in March 2020, was created to provide financial support to small businesses during the COVID-19 pandemic. Numerous studies have examined the program's efficacy, including several papers that have studied racial disparities in the program (Chernenko and Scharfstein, 2023; Howell et al., 2024; Fei, 2022; Atkins, Cook, and Seamans, 2022a,b; Erel and Liebersohn, 2022; Wang and Zhang, 2020). This body of work has documented three key facts. First, Black-owned firms are less likely than observably similar white-owned firms to receive PPP funds (Chernenko and Scharfstein, 2023). Second, conditional on receiving a PPP loan, Black-owned firms are less likely to receive their loans from banks and more likely to receive them from nonbanks, largely fintech lenders (Chernenko and Scharfstein, 2023; Howell et al., 2024; Fei, 2022). Third, racial bias partly explains why Black-owned firms are less likely to receive PPP loans from banks (Chernenko and Scharfstein, 2023; Howell et al., 2024).

Because publicly available PPP data only include information on approved loans, prior work has been largely unable to assess whether these three facts are driven by application behavior or by loan approval outcomes. Consequently, our understanding of the economic mechanisms driving these disparities remains limited, as does our understanding of the role that fintech lenders play in expanding access to credit more generally. Several important questions remain unanswered. How much of the take-up disparity is due to racial disparities in PPP demand, awareness of the program, or program eligibility (either actual or perceived)? To the extent that take-up disparities are driven by approval disparities, why are there any approval disparities when lenders bear no credit risk? Do fintechs increase PPP access for Black-owned businesses by lowering application barriers relative to banks or by better facilitating loan approvals for eligible Black-owned applicants? Finally, does the documented effect of racial bias on take-up of bank loans reflect a reluctance of Black-owned firms to apply to banks, or biased loan approval decisions by bank loan officers? Answering these questions is essential for understanding the root causes of disparities in the PPP and for designing effective interventions to improve access to future programs with similar objectives.

We use novel survey data on PPP application choices and approval outcomes to answer these questions. We report four main findings. First, we show that the disparity between Black- and white-owned firms in the likelihood of applying for PPP loans explains just over half of the overall disparity in program take-up, with approval disparities explaining the rest. Second, we find that application behavior fully explains why Black-owned firms are less reliant on banks and more reliant on fintech lenders for PPP loans. In particular, we show that Black-owned firms are substantially less likely than observably similar white-owned firms to apply to banks and substantially more likely to apply to fintechs, but that racial disparities in approval rates are very similar at banks and fintechs. Third, racial bias negatively affects the take-up of bank PPP loans by Black-owned firms through its effect on both applications and approvals; Black-owned firms are less likely to apply to banks and more likely to apply to fintechs in more racially biased counties, and their applications are less likely to be approved by banks (but not fintechs) in those counties. Fourth, we find no evidence that either application or approval disparities are driven by differential demand or program eligibility. Instead, we find strong evidence that procedural issues in the application process (e.g., submitting all required documentation) are an important cause of both application disparities as well as bank and fintech approval disparities.

Our data come from the Federal Reserve's 2020 Small Business Credit Survey, which asked over 15,000 small businesses about their finances and their use of the PPP and other emergency support programs. Importantly, the survey includes information on whether each firm applied for a PPP loan, whether it ultimately received a PPP loan, the type of lender to which the firm applied and from which it received a loan, and whether it received the total amount requested. The survey also includes detailed information on firm and owner characteristics, including race, Hispanic origin, and gender, thus obviating the need to infer these characteristics indirectly and imperfectly from data such as names and locations. Therefore, the survey data are well-suited for the study of racial disparities in both PPP applications and approvals.

To begin our analysis, we demonstrate the accuracy and validity of our survey data by showing that the three main findings in the existing literature (Chernenko and Scharfstein, 2023; Howell et al., 2024) hold in our sample. We first show — consistent with Chernenko and Scharfstein (2023) — that Black-owned firms are significantly less likely than observably similar white-owned firms to receive PPP loans. Second, conditional on receiving a PPP loan, Black-owned firms are less likely than observably similar white-owned firms to receive a PPP loan from a bank and more likely to receive it from a fintech lender. We also show — consistent with Chernenko and Scharfstein (2023) and Howell et al. (2024) — that this substitution from banks to fintechs is stronger in more racially biased counties. Although we use very different data, our estimates of racial disparities in PPP take-up are remarkably similar to those in Chernenko and Scharfstein (2023). In particular, we find that unconditionally Black-owned firms are 25.7 percentage points less likely to receive PPP loans, as compared to a disparity of 25.5 percentage points documented by Chernenko and Scharfstein (2023) in their sample of Florida firms. Controlling for a rich set of observable firm and owner characteristics, we estimate that Black-owned firms are 8.9 percentage points less likely to receive a PPP loan, whereas Chernenko and Scharfstein (2023) estimate a disparity of 9.2 percentage points when controlling for a different set of characteristics.

To what extent does the disparity in application rates between Black- and white-owned firms explain this 8.9 percentage point disparity in take-up? After controlling for observable firm and owner characteristics, we find that Black-owned firms are 4.9 percentage points less likely to apply for a PPP loan. The application disparity can therefore explain about 55% (4.9/8.9) of the take-up disparity between observably similar Black- and white-owned firms, while the disparity in approval rates explains the rest. Differences between Black- and white-owned firms in whether they have a relationship with a bank can only partially explain the application disparity, reducing it from 4.9 to 3.8 percentage points. County-level measures of explicit and implicit racial bias are likewise unable to explain this application disparity.

To better understand why Black-owned firms are less likely to apply for PPP loans, we leverage a survey question that asks firms that did not apply why they chose not to do so. We find that the racial disparity in the PPP application rate is not driven by differential demand; conditional on our full set of controls, Black-owned firms are 7.4 percentage points less likely than white-owned firms to state that they did not need funding. Furthermore, Black-owned firms are 2.1 percentage points less likely to indicate that they did not apply because they were not interested in government aid. We likewise find no evidence that Black-owned firms are more likely to be concerned about eligibility for the loan or for loan forgiveness. Nor are Black-owned firms more likely to state that they had difficulty finding a lender willing to accept their application. What we do find is that Black-owned firms are more likely than observably similar white-owned firms to say they did not apply because the process was too confusing (5.8 percentage point differential), they were unaware of the program (4.7 percentage point differential), or they missed the program deadline (7.4 percentage point differential). The evidence thus suggests that application disparities are driven to an important extent by the program's "administrative burdens" that may have disproportionately affected Black-owned businesses. Indeed, Herd and Moynihan (2018) argue that administrative burdens – the costs associated with obtaining benefits from a public program – reduce take-up of a broad range of government programs and that these burdens can affect disadvantaged groups more acutely. Such costs include the time and effort needed to understand and assess a program's advantages and risks. They also include the time and effort to prepare and organize the documents required for the application and to correctly fill out the application form according to program rules. Given the complex documentation requirements of the PPP, which we detail in the Appendix, and changing PPP rules around both eligibility and allowable loan amounts, the administrative burdens of the PPP were considerable.[1]

In addition to the disparity in PPP application propensity, there are differences in the types of lenders to which Black- and white-owned firms apply. We find that when Black-owned firms do apply for a PPP loan, they are 16.5 percentage points less likely to apply to banks and 14.7 percentage points more likely to apply to fintechs. Firm characteristics — in particular revenues, firm size, and firm age — account for almost half of this sorting; Black-owned firms are 9.9 percentage points less likely than observably similar white-owned firms to apply to banks and 7.8 percentage

[1] While we argue that these administrative burdens reduced PPP take-up, particularly for Black-owned firms, they may also have reduced fraud by screening out fictitious businesses and applications for excessive loan amounts (Aman-Rana, Gingerich, and Sukhtankar, 2022). Griffin, Kruger, and Mahajan (2022) use a variety of indicators to estimate the percentage of PPP loans that are potentially fraudulent.

points more likely to apply to fintechs. Our estimate of sorting is robust to including a control for whether a firm has a bank relationship, even though bank relationships increase the likelihood that firms apply for PPP loans from banks and white-owned firms are more likely to have bank relationships. Furthermore, Black-owned firms are especially unlikely to apply to banks relative to fintechs in counties where there is more racial bias toward Black people. In counties that are one standard deviation above the nationwide mean of implicit racial bias, as measured by Project Implicit, Black-owned firms are 20.8 percentage points less likely than observably similar white-owned firms to apply to banks and 17.6 percentage points more likely to apply to fintechs.

These findings suggest either that a legacy of racial discrimination by banks discouraged Black-owned businesses from approaching banks for PPP funding or that when they approached banks, they were discouraged from applying due to the racial animus of loan officers. In contrast, given the automated nature of fintech lending, it is unlikely that racial animus would have limited applications by Black-owned firms to fintechs. Indeed, given our evidence that Black-owned firms experienced greater administrative burdens in the application process, it is possible that the more streamlined application process at fintechs attracted more applications from Black-owned firms.

We next show that while there are large differences between Black- and white-owned firms in their propensity to apply to banks versus fintechs, the disparities in loan approval rates are similar at banks and fintechs. Compared to observably similar white-owned firms, applications from Black-owned firms are 7.4 percentage points less likely to be approved at banks and 8.4 percentage points less likely to be approved at fintechs. Thus, the lower reliance of Black-owned firms on bank-intermediated PPP loans documented in prior work is driven entirely by the fact that Black-owned firms are less likely to apply to banks and more likely to apply to fintechs.

Why are there approval disparities at banks and fintechs? For banks, at least part of the answer is related to racial bias, as Black-owned firms are significantly less likely to be approved in more racially biased counties. But this is probably not the whole explanation. The approval disparity at fintech lenders is similar in magnitude to the approval disparity at banks, even though fintech disparities are unlikely to be significantly affected by racial bias due to the largely automated nature of fintechs' approval processes. We present evidence that just as the administrative burdens inherent in the PPP application process led to lower application rates by Black-owned firms, they may also have led to racial disparities in approval rates. Although the overwhelming majority of loan applications from Black- and white-owned firms were approved, there are numerous accounts of difficulties that small firms faced in documenting their eligibility for the program, determining the loan amounts they could request under program rules, and substantiating their requested loan amounts with required documentation. There is also considerable anecdotal evidence from congressional testimony and interviews suggesting that Black-owned firms faced greater challenges meeting documentation requirements and determining the loan amounts they could request under program rules. Indeed, many organizations started initiatives to help Black-owned firms with the application process to address the concern that Black-owned firms received less support from loan officers and professional services providers in preparing their applications. This is consistent with evidence from the 2021 Small Business Credit Survey indicating that Black-owned firms are significantly less likely than white-owned firms to seek business advice from professionals such as lawyers, accountants, and consultants, even after controlling for detailed firm and location characteristics.

We directly test this hypothesis with our survey data by asking whether, conditional on receiving PPP funds, Black-owned firms are less likely to receive the full amount for which they applied. Our design leverages the fact that, given the PPP's formulaic procedure governing eligible loan size, there are only three reasons why a firm would receive less funding than it applied for: (i) taking only some of the granted funding (e.g., due to concerns or uncertainty about the loan forgiveness process); (ii) requesting more than the maximum amount for which the firm is eligible; and (iii) being unable to produce documentation substantiating components of the total amount requested. We argue that that the first explanation is unlikely, given our evidence that Black-owned firms if anything have higher demand for funds and given previously-documented evidence that Black-owned firms are particularly likely to obtain Economic Injury Disaster Loans (EIDL) (Chernenko and Scharfstein, 2023), which are not forgivable. Thus, finding that Black-owned PPP recipients are less likely to receive the full amount they requested would implicate reasons (ii) and (iii), both of which fall under our definition of administrative burden. This is exactly what we find: 79% of all firms receiving bank PPP loans receive their full request, but the disparity between observably similar Black- and white-owned firms is 20.3%. While in principle, it is possible that some or all of this disparity is driven by racially-biased loan officers systematically disputing the loan calculations submitted by Black-owned firms (though they also would have to approve said applications in order to do so), we do not find any correlation between our racial bias measures and the magnitude of this disparity. Moreover, we obtain very similar results within the sample of fintech PPP recipients: 62% of all firms receiving fintech PPP loans receive their full request, but the disparity between observably similar Black- and white-owned firms is 25.3%. To the extent that lenders are less likely to approve applications with either erroneous requested amounts or missing documentation, these results strongly indicate that a disparate impact of administrative burdens on Black-owned firms helps to explain the large approval disparities that we estimate at both banks and fintechs.

Prior work has documented the ways in which fintechs use technology to improve credit decisions. For example, fintechs process "conventional" and "unconventional" data to assess the credit risk of lending to borrowers with thinner credit histories (Di Maggio and Ratnadiwakara, 2024). Further, by automating the lending process fintechs may reduce the scope for racial bias in consumer lending (Bartlett et al., 2022) and PPP lending (Howell et al., 2024), consistent with our results. However, our finding that PPP approval disparities are similar in magnitude at banks and fintechs raises important new questions about the relationship between automation and credit access for under-banked people and firms.[2] In particular, the less personalized approval process at fintechs — some fintechs processed most of their applications without any human involvement[3] — may have reduced their ability to ease administrative burdens in the loan approval process, thereby limiting loan access for applicants with fewer resources to navigate the application process. By comparison, the more hands-on and interactive approach of banks may have better positioned them to help applicants resolve documentation gaps and determine the correct loan amounts, even as it increased the scope for racial bias to affect approvals. In fact, while approval disparities at banks are greater in more racially biased areas, we find no meaningful approval disparities at banks in less racially biased locations, consistent with the possibility that loan officers in these areas may have helped Black-owned applicants source the documentations required for PPP loan approval.[4] By contrast, fintechs may not have had enough employees to be responsive to the questions of individual applicants or address their specific application issues. As one Forbes article states, "Working with FinTech firms is still a nameless, faceless process. Some small business owners found the automation a frustrating aspect of the PPP loan process. There are numerous stories of individuals who should have been able to access PPP but were rejected by FinTech firms, with the only recourse being a 1-800 number."[5] Given that Black applicants likely faced greater administrative burdens, the limited ability of fintechs to respond to their questions may help explain approval disparities at fintechs.

Our findings also relate to the literature on administrative burdens in public programs. Wu and Meyer (2021) present causal evidence that automating SNAP and Medicaid enrollment processes reduced take-up of both programs. This finding is consistent with the idea that there are administrative burdens associated with automated processes. Other work has studied the costs and benefits of reducing administrative burdens in a variety of public programs. In the context of the PPP, Aman-Rana, Gingerich, and Sukhtankar (2022) use time-series variation in application documentation requirements to show that additional screening reduced fraud, while Humphries,

[2] Howell et al. (2024) find no racial disparities in PPP approval rates at fintechs in a sample of applications received by Lendio, a marketplace lending platform. However, Howell et al. (2024) indicate that the "application through Lendio included all necessary components and was screened for completeness." This screening by Lendio is a key factor in explaining the difference in results in the two papers. Thus, while we calculate approval rates conditional on applying, their analysis conditions on firms being able to provide all necessary documentation.

[3] Kabbage PPP results: A Historic Feat for Fintech, August 8, 2020, at `https://newsroom.kabbage.com/wp-content/uploads/2020/08/Kabbage-Paycheck-Protection-Program-PPP-Report.pdf`.

[4] This interpretation is consistent with Frame et al. (2022), who show that mortgage applications of minority borrowers are more likely to be completed and approved if the application is handled by a minority loan officer. Frame et al. (2022) argue that minority loan officers may put more effort into helping minority applicants secure the documentation they need.

[5] Megan Gorman, Why FinTechs Are Declaring Victory in PPP Loans, August 13, 2020, at `https://www.forbes.com/sites/megangorman/2020/08/13/why-fintechs-are-declaring-victory-in-ppp-loans/?sh=591271632205`.

Nielsen, and Ulyssea (2020) and Bartik et al. (2020) present survey evidence consistent with a disproportionate impact on smaller firms of the administrative burdens of the PPP. In particular, Humphries, Nielsen, and Ulyssea (2020) find that smaller firms are less likely to be aware of the PPP and also less likely to apply for a PPP loan. Conditional on applying, the authors show that smaller firms apply later, wait longer to receive approval decisions, and are less likely to be approved. Using data from a different survey, Bartik et al. (2020) show that larger firms are more likely to have their PPP applications approved. In the context of other public programs, Bettinger et al. (2012) present experimental evidence that assisting low-income students with federal student aid applications increased application rates, likelihood of aid receipt, college attendance, and college completion. Finkelstein and Notowidigdo (2019) likewise use an experiment to show that providing eligibility information and application assistance increased SNAP take-up. Relative to these studies, our results demonstrate that even in a program specifically designed to have streamlined application and approval processes, administrative burden can still generate sizable racial disparities in take-up. Thus, the trade-off between screening and access is only one piece of the puzzle; it is equally important to find and address issues further upstream, such as disparities in access to financial advisory services.

To the best of our knowledge, only one other paper has used the Small Business Credit Survey to study the Paycheck Protection Program (Barkley and Schweitzer, 2023). Although their focus is on racial disparities in standard credit products (i.e., non-emergency) between 2016 and 2020, Barkley and Schweitzer (2023) also find that Black- and Hispanic-owned businesses with paid employees are less likely than white-owned businesses with paid employees to get the full requested PPP loan amount. Our results demonstrate that this result is due to both an extensive margin (approval for any credit) and an intensive margin (being approved for less funds than requested), showing that both are quantitatively important.[6] More importantly, we are the first paper to use SBCS microdata to understand the differences between banks and fintechs in the application and approval process, and how these differences alleviate or exacerbate disparities in program outcomes.

Our paper is organized as follows. In the next two sections, we provide institutional background on the PPP and then describe the data. In Section 4, we first replicate key findings of the literature on racial disparities in the PPP using data from the Small Business Credit Survey, and then we present our main results on application and approval disparities. Section 5 argues that in addition to observable characteristics and racial bias, the disparate impact of administrative burdens is likely to play a role in our findings on racial disparities. Section 6 concludes.

[6] Distinguishing between these two channels is important: a firm may receive less funds than they requested because they inadvertently requested more than they were eligible for, in which case they could very well end up receiving the correct amount of funds under program rules; an eligible firm receiving no funds necessarily missed out on funds they should have received.

2 An Overview of the Paycheck Protection Program

Initially authorized in March of 2020 by the CARES Act, the Paycheck Protection Program offered qualifying small businesses non-recourse loans with standardized terms and the possibility of full or partial forgiveness. Loans were originated and underwritten by a variety of financial intermediaries, including depository institutions, fintechs, and Community Development Financial Institutions (CDFIs). Lenders retained no credit risk on the loans, as the federal government fully guaranteed all loans regardless of whether the loans were forgiven. There were few eligibility requirements, as one of the program's goals was to include the vast majority of businesses with fewer than 500 employees. In 2020, maximum eligible loan amounts were based on 2019 net profits (for firms without employees), 2019 payroll costs (for corporations), or both (for firms with self-employed owners, where net profits served as a proxy for "Owner Compensation Replacement").[7]

As part of the application process, the SBA required a number of documents to substantiate payroll costs and to prove that a business was operating as of February 15, 2020. After choosing a lender, firms were required to submit the SBA application, Form 2483, along with forms of owner identification, proof of business existence as of February 15, 2020 and documentation to substantiate the loan amount calculations underlying the PPP amount requested on Form 2483.[8] In most cases, owners submitted driver's licenses for identification purposes. To prove that a business actually existed and to support loan amount requests, lenders typically required applicants to submit recent bank statements and federal tax returns. The Appendix describes documentation requirements in greater detail.

If a firm applied to a depository institution with which they did not have a pre-existing relationship, the depository institution was required to perform additional reviews in order to satisfy Anti-Money-Laundering (AML) and Bank Secrecy Act (BSA) regulations. The SBA also required non-depository financial institutions to establish "comparable" compliance systems with respect to their own PPP processes.[9]

For applicants meeting all of the lender's application requirements, lenders submitted loan

[7] SBA, Paycheck Protection Program How To Calculate Maximum Loan Amounts – By Business Type, April 24, 2020, at https://web.archive.org/web/20200807154011/https://www.sba.gov/sites/default/files/2020-04/How-to-Calculate-Loan-Amounts.pdf; SBA, How to Calculate First Draw PPP Loan Amounts, March 12, 2021, at https://www.sba.gov/document/support-how-calculate-first-draw-ppp-loan-amounts.

[8] SBA, Paycheck Protection Program Borrower Application Form, April 2, 2020, at https://www.sba.gov/sites/default/files/2022-02/PPP-Borrower-Application-Form-Fillable.pdf; SBA, Paycheck Protection Program Borrower Application Form Revised March 18, 2021, March 18, 2021, at https://www.sba.gov/document/sba-form-2483-ppp-first-draw-borrower-application-form.

[9] Rules and Regulations, Federal Register Volume 85, Number 73, pages 20811-20817, April 15, 2020, at https://www.govinfo.gov/content/pkg/FR-2020-04-15/pdf/FR-2020-04-15.pdf

requests to the SBA through the latter's E-Tran processing software. The software would then scan loan requests for missing or incorrect fields, returning error codes for requests with unresolved issues and returning loan identification numbers for approved requests. The SBA did not review any borrower or loan information before approving loans in 2020 other than screening for duplicate PPP applications.[10] After receiving a loan number from the SBA, lenders were cleared to proceed with closing documentation and disbursement of funds. In 2021, the agency began running all loan requests through an automated screening procedure to verify program eligibility.[11]

As discussed above, legislators intended for PPP loans to be accessible to the vast majority of active small businesses (subject to exceptions for certain industries and affiliation structures). Nevertheless, the legislation retained many eligibility requirements from existing SBA lending programs.[12] For example, firms employing household workers (e.g., caretakers) were not eligible for PPP based on existing SBA rules. Further, the SBA listed additional disqualifying considerations related to credit and criminal history on SBA Form 2483. We discuss these conditions in more detail in Section 6. Form 2483 explicitly stated that applicants checking yes to any of these stipulations would be denied automatically.

3 Data

The main data source for our study is the Federal Reserve's 2020 Small Business Credit Survey (SBCS). We supplement these data with (i) ZIP code characteristics from the U.S. Census' 2019 American Community Survey (5-year estimates); (ii) ZIP code-level information on bank branches from the FDIC's 2020 Summary of Deposits; (iii) county-level information on explicit and implicit bias towards Black people from Harvard University's Project Implicit.

[10] US GAO Report 21-577 to Congressional Addressees, Paycheck Protection Program: SBA Added Program Safeguards, but Additional Actions Are Needed, July, 2021, page 16, at https://www.gao.gov/assets/gao-21-577.pdf.

[11] Ibid. and SBA, Procedural Notice 5000-20092, February 10, 2021, at https://www.sba.gov/sites/default/files/2021-02/Procedural%20Notice%205000-20092%20-%20Revised%20PPP%20Procedures%20to%20Address%20Hold%20Codes-508_0.pdf.

[12] Code of Federal Regulations, 13 CFR 120.110, What Businesses Are Ineligible for SBA Business Loans, as amended June 30, 2022, at https://www.ecfr.gov/current/title-13/chapter-I/part-120/subpart-A/subject-group-ECFR6d9c2c4fd6e44c1/section-120.110. Note that not all of these requirements were applied to the PPP. Non-profits, for example, were eligible for PPP loans.

3.1 Small Business Credit Survey

The SBCS is an annual, collaborative effort among the twelve Federal Reserve Banks.[13] The Reserve Banks work with over 100 community organizations (including chambers of commerce, government agencies, and development corporations), each of which emails small business owners and employees in their respective network, inviting them to complete the survey. The Reserve Banks also reach out via email to previous survey respondents. Other interested small business owners and employees can find links to the survey on the websites of the Reserve Banks. Because the SBCS is conducted by the Federal Reserve's member banks, it is highly likely that the survey's respondents are legitimate businesses. This differentiates our sample from the population of PPP borrowers, which Griffin, Kruger, and Mahajan (2022) show includes many fictitious firms that received funding based on fraudulent representations. [14] Thus, our sample likely does not include firms that engaged in criminal activity in an attempt to receive PPP funds for which they knew they did not qualify.

Responses are collected in September and October of each year and then undergo a rigorous screening process to ensure data accuracy.[15] The Federal Reserve System publishes a series of reports about the data over the course of the following year to spotlight survey outcomes for particular populations of interest (e.g., employer firms, nonemployer firms, and minority-owned businesses). The SBCS website provides data appendices that cross-tabulate respondent answers by various characteristics of interest, though individual responses are kept confidential. All statistics published on the SBCS website are weighted on a variety of firm characteristics in order to achieve a representative national sample. We report unweighted estimates as our main results, with analogous weighted estimates included in the Internet Appendix.[16] We make this choice for three main reasons. First, as mentioned above, the weights are designed to achieve national representativeness among all small businesses. However, many of our analyses are conducted in subsamples of the population (e.g., among firms submitting PPP applications to banks) – these subpopulations likely differ in important ways from the overall population, so using weights that reflect the overall population is not appropriate. Morever, we would not be able to construct our own weights for these subpopulations because the distributions of characteristics among many of these subpopulations

[13] Fed Small Business, at https://www.fedsmallbusiness.org

[14] See also the US House Select Subcommittee on the Coronavirus Crisis, How Fintechs Facilitated Fraud in the Paycheck Protection Program, December 1, 2022, at https://coronavirus-democrats-oversight.house.gov/sites/democrats.coronavirus.house.gov/files/2022.12.01%20How%20Fintechs%20Facilitated%20Fraud%20in%20the%20Paycheck%20Protection%20Program.pdf

[15] Among other things, staff members check for multiple responses by the same firm and remove firms that do not provide information on their ZIP code, number of employees, or year of establishment.

[16] Because we do not weight our data, our samples tend to be slightly larger than the analogous ones underlying the online reports.

are unknown. Second, the SBCS weights involve imputing demographic information, including racial and ethnic identities, for almost 10% of survey respondents. The well-populated nature of the self-reported demographic information is a crucial advantage of this data, one which would be greatly weakened by introducing this imputation error into our estimates. Finally, the SBCS constructs weights separately for employer businesses and nonemployer businesses, making it difficult to interpret the results of any analysis that pools both types of firms.

Since achieving national coverage in 2016, the SBCS has maintained a similar format and set of questions from year to year in the interest of longitudinal comparability. Each year's questionnaire includes sections on firm demographics, performance, financing applications and outcomes, owner demographics, and an optional "special topic" portion that changes each year. The survey is intended to take about ten minutes to complete and follows a "branching process," in which respondents are directed to complete different modules based on their answers to particular questions. For example, firms that report applying for financing in the previous twelve months are asked for more information about their most recent applications, whereas firms that did not apply are asked about their decision not to apply.

3.2 2020 SBCS

The 2020 survey deviates substantially from past surveys in its focus on the Covid-19 pandemic. New sections include "Impact of the Covid-19 Pandemic," "Emergency Assistance Related to the Covid-19 Pandemic," and an optional special topic module that asks additional questions about the pandemic's impact.[17] Many sections that are not unique to the 2020 survey also incorporate new questions about the pandemic.

The SBCS microdata contains 15,234 responses deemed "usable" by the screening process. Included businesses span all 50 states and the District of Columbia. Figure A.2 reports two heat maps showing i) each state's share of total respondents to the 2020 SBCS and ii) each state's share of total U.S. establishments per the Census' 2018 County Business Patterns and Nonemployer Statistics Combined Report. Internet Appendix Figure IA1 complements Figure A.2 by showing a scatter plot of each state's 2020 SBCS share against its Census share. The correlation between the two is about 0.63. Together, Figures A.2 and IA1 show that the distribution of responding firms across states is broadly representative of the overall population of U.S. employer and nonemployer establishments.

As seen in Table A.1 and Internet Appendix Table IA1, the distribution of survey respondents across industries is also similar to the overall population of establishments. Non-manufacturing

[17] See Figure A.1 for an illustration of the 2020 survey's structure.

Goods Production & Associated Services (NAICS: 11, 21, 22, 23, 42, 48–49) is moderately under-represented, and both Manufacturing (NAICS: 31–33) and Leisure and Hospitality (NAICS: 71, 72) are over-represented. These deviations are due in part to industry composition differences between employer and nonemployer firms and the slight over-representation of employer firms in our sample. Differences in the industry distributions by firm size also help to explain the difference between the sample industry distribution and the overall sample of establishments.

Although the survey does not perfectly the match the geographic and industrial composition of the overall population of establishments, we show in Section 4.1 that the survey data replicate the key findings on racial disparities in the PPP documented by the prior literature. In particular, our estimates of both unconditional and conditional disparities in PPP take-up are extremely similar to Chernenko and Scharfstein (2023), who use data on the take-up of PPP by the population of Florida restaurants. The results in Section 4.1 thus help to further validate the accuracy of survey responses and mitigate any concerns about sample selection.

3.3 Owner Demographics and Firm Characteristics

Well over 90% of surveyed firms provide detailed information on the racial, Hispanic, and gender identities of their owners. Together with information about the equity stakes of each owner of a firm, we are able to identify minority- and female-owned businesses with a very high degree of accuracy.

We follow standard practice in defining minority- and female-owned businesses. Firms with at least a 51% equity stake held by owners identifying as members of group g are classified as being g-owned businesses, where $g \in$ {Black, Hispanic, Asian, Native American, Middle Eastern/North African, Other Race, Female}. Owners are permitted to identify with multiple categories, and for owners that do we include them in each group with which they identify, provided they own at least 51% equity.[18] Finally, following the Census approach, we define white-owned firms as businesses with at least a 50% equity stake held by non-Hispanic white owners.

Because a very small fraction of firm owners identify themselves as Native American, Middle Eastern/North African, or Other, we include these owners in our analysis but do not report results for these groups. While excluding these indicator variables would not materially affect the results, we prefer to include them in order to maintain the interpretation that all Black-, Asian-, and Hispanic-owned firms' outcomes are relative to a baseline of white-owned firms. Our analysis excludes less than 1% of the firms in the sample for which no racial or ethnic group of owners has a majority equity stake.

[18] In practice, only about 5% of firms for which we have racial/ethnic information are considered to be owned by individuals from multiple racial/ethnic groups.

The survey database includes other useful data on surveyed firms: number of current owners; the number of full-time employees and number of part-time employees as of January 1, 2020; 2019 revenues; 2019 profitability (i.e., "Loss," "Break-Even," or "Profit"); the age of the primary owner; and use of contract workers in the past 12 months (yes/no). One of the strengths of the survey is that most of this information reflects business characteristics prior to, and therefore independent of, the Covid-19 pandemic.[19]

3.4 PPP Outcomes

The SBCS asks businesses a number of questions about the PPP, of which seven are of particular interest to us. First, the survey asks all firms whether they applied for PPP loans. Second, the survey asks non-applicants to choose the reasons they did not apply. Response options include, but are not limited to: "was unaware of the program," "program/process was too confusing," and "business would not qualify for the loan or loan forgiveness."

Third, the survey asks applicants about the types of lenders to which they submitted their PPP applications. Some applicants may have applied to more than one type of lender. The question lists seven possible lender types: large bank, small bank, online/fintech lender, finance company, credit union (CU), community development financial institution (CDFI), and "other lender." We distill these categories into three mutually exclusive and exhaustive lender types: banks (made up of large and small banks), fintechs (made up of online/fintech lenders, finance companies, and "other lenders"), and CU/CDFI.[20] The choice to include finance companies and "other lenders" in our fintech category is in large part informed by the result (based on a fuzzy merge of our data with the PPP administrative data) that about 70% of PPP recipients listing finance companies or "other lender" as lender type in the SBCS received their loans from lenders better categorized as fintechs.[21] Unfortunately, respondents are far less consistent in their distinctions between "large" and "small" banks, in part because the survey does not provide respondents with a formal definition of either term. As a result, we combine these lender categories into a single "bank" classification.

Fourth, the survey asks whether applicants had existing bank relationships prior to submitting their application to each chosen lender type. While the survey does not provide a definition of

[19] Firms provide other relevant information, such as business and personal credit scores at the time of the survey, but we do not use these data in our analysis because they could be affected by the PPP outcomes we are trying to explain.

[20] In practice, some fintech companies partnered with fintech banks (e.g., Cross River Bank, Celtic Bank) in the origination process: the fintech company would process the application and the bank would fund the loan and hold it on its balance sheet.

[21] In total, about 88% of firms that we code as receiving fintech PPP loans and are able to match to the PPP administrative data received loans from lenders that we would classify as fintechs.

"relationship," survey responses suggest that most firms interpreted a relationship to mean having a checking/savings account, business credit card, or loan/line of credit. Fifth, applicants are asked to provide the amount of funds they requested in their PPP application. Sixth, PPP applicants are asked about the type of lender from which they either received their loan or where their application was "most complete."[22]

Finally, PPP recipients are asked for the amount of PPP funding they actually received. We classify firms receiving $0 as those that were not approved and firms receiving a positive amount of PPP funding as those that were approved. It is important to note that we cannot confirm whether "not approved" firms were actually rejected, never heard back about their application, or withdrew their application before hearing back. Firms applying to multiple lender types are marked as approved (not approved) by the lender type from which they received (did not receive) funding. As a result, approval outcomes should be interpreted slightly differently in the context of specific lender types relative to approval for any PPP loan. However, we show in Internet Appendix Table IA3 that approval disparities are not meaningfully affected by controlling for whether firms applied to multiple lender types, suggesting that neither fintech nor bank approval disparities are driven by Black-owned firms being particularly likely to find another lender while waiting for their application to be processed. For additional information on the mapping between survey questions and our derived variables, see Table A.2.

3.5 Project Implicit

Project Implicit provides a variety of free online "Implicit Association Tests," each of which measures a test-taker's bias against a particular group of people (e.g., Black people, older people, transgender people).[23] One of the bias measures we use is an implicit bias measure, defined as the strength of an implicit preference for white people over Black people. We also use an explicit bias measure, which is derived from a question at the conclusion of the test asking people to rate, on a 1-7 scale, the strength and direction of their preference for Black people versus white people: 1 is "I strongly prefer African Americans to European Americans", 4 is "I like European Americans and African Americans equally", and 7 is "I strongly prefer European Americans to African Americans."

Project Implicit provides county-level information on test results by race of the test-taker. Using only results from tests taken by white people between 2008 and 2019, we construct our county-level "implicit bias" measure using average results from the Implicit Association Test, and

[22] From the responses to this question, we isolate actual PPP recipients in order to avoid mistakenly marking non-recipient firms that list a "most complete" lender type as approved firms.

[23] Project Implicit Preliminary Information, Harvard University, at https://implicit.harvard.edu/implicit/takeatest.html

we construct our county-level "explicit bias" measure using average responses to this question asked at the conclusion of the test. Figure A.3 displays the county-level distribution of the implicit and explicit bias measures, each of which is standardized to have zero mean and unit variance.

3.6 Supplemental Data Sources

We obtain information on ZIP code characteristics from the 2019 American Community Survey's 5-year estimates. These characteristics include population, the fraction of the population that is non-Hispanic white, the unemployment rate, and median household income. Using the FDIC's 2020 Summary of Deposits, we calculate the number of commercial bank branches per 1000 people in each ZIP code.[24]

3.7 Summary Statistics

Table 1 displays the means of our variables. About 71.1% of firms are white-owned, 14.0% are Black-owned, 6.4% are Asian-owned, and 8.5% are Hispanic-owned. Just under 60% of firms are either male-owned or equally-owned.

Across virtually all firm characteristics, there are substantial differences in the means of different demographic groups. Relative to minority- and female-owned businesses, respectively, white-owned and male-/equally-owned businesses: (i) are far larger and older; (ii) have higher revenues; and (iii) are more likely to be profitable. In all cases, the starkest differences are between white- and Black-owned firms. Of particular note, Black-owned businesses are half as likely to have revenues exceeding $100k (37% of Black-owned businesses versus 74% of white-owned businesses) and two-thirds as likely to be profitable (44% of Black-owned businesses compared to 66% of white-owned businesses).

White- and Black-owned businesses, and to a lesser extent other minority-owned businesses, also tend to be located in ZIP codes with different characteristics (though the same is not the case for male- and female-owned businesses). On average, Black-owned businesses are located in ZIP codes with larger populations but fewer bank branches per capita than white-owned businesses. On average, ZIP code-level median household income is about 15% lower for Black-owned firms, and the average unemployment rate is moderately higher.

Consistent with prior academic research, press accounts, and the Federal Reserve's own reports using 2020 SBCS data, the final section of the table illustrates striking differences in both PPP application behavior and approval outcomes between firms with different ownership demographics.

[24] Results are virtually unchanged when we use the 2019 Summary of Deposits.

Black- and Hispanic-owned businesses are substantially less likely than white-owned businesses to apply for PPP funds (49% and 62% of Black- and Hispanic-owned firms, respectively, compared to 71% of white-owned firms). Female-owned firms are also less likely than male-/equally-owned firms to apply (63% versus 70%). Furthermore, conditional on applying, Black- and Hispanic-owned firms are less likely than white-owned firms to apply through banks and more likely to apply through fintechs.

Black- and Hispanic-owned businesses that apply for PPP loans are markedly less likely than white-owned businesses to receive PPP funding. Conditional on applying for PPP, 95% of white-owned firms receive PPP funding, whereas 81% of Black-owned businesses receive funding, and 90% of Hispanic-owned firms receive funding. In the next sections, we study the sources of these application and approval disparities.

4 PPP Applications and Approvals

4.1 Replication of Prior Findings in the SBCS Sample

We start our analysis by showing that three key findings on racial disparities in the PPP documented by the prior literature carry over to our SBCS sample, thereby helping to validate the accuracy of survey responses about PPP applications and approvals. First, we show that Black-owned firms are less likely to receive PPP loans (Chernenko and Scharfstein, 2023). Second, among PPP recipients, Black-owned firms are less likely than white-owned firms to receive PPP loans from banks and more likely to receive PPP loans from fintechs (Chernenko and Scharfstein, 2023; Howell et al., 2024). Third, in more racially biased counties, Black-owned firms are even less likely to receive PPP loans from banks and even more likely to receive funding from fintechs (Chernenko and Scharfstein, 2023; Howell et al., 2024).

In the first two columns of Table 2, we report the results of linear probability models in which the dependent variable is a binary variable equal to one if a firm receives a PPP loan and equal to zero otherwise. The only regressors in the first column are the indicator variables for race/ethnicity and gender. We only show results for Black, Asian, Hispanic, and female owners, suppressing the coefficients for the other race/ethnicity indicator variables (Native American, Middle-Eastern/North-African, and Other) given their relatively small share of the sample. The coefficients of the Black, Asian, and Hispanic indicator variables measure the incremental likelihood of receiving a PPP loan relative to the excluded group of firms owned by white people; the coefficient on the female indicator variable measures the incremental likelihood of receiving a PPP loan relative to the excluded group of firms either owned by men or equally owned by men and women. Black-owned, Hispanic-owned and female-owned firms are 25.7 percentage points, 8.4 percentage points and 5.4 percentage points less likely, respectively, than white-owned firms to receive a PPP loan. All three estimates are highly statistically significant. Asian-owned firms are 5.5 percentage points more likely than white-owned firms to receive a PPP loan, and this estimate is also statistically significant.

The second column of Table 2 adds controls for firm, owner and ZIP code characteristics, as well as state and industry fixed effects. Because PPP eligibility was tied directly to profitability for nonemployer firms but not for employer firms, we allow profitability to have different effects for employer and nonemployer firms. Including our controls reduces the estimated disparities in PPP take-up for Black- and Hispanic-owned firms to 8.9 percentage points and 6.1 percentage points, respectively, though both estimates remain highly statistically significant. After including the controls, the difference in the take-up rate between Asian-owned and white-owned firms is no longer statistically different from zero, and female-owned firms are 2.9 percentage points more likely than observably similar male-owned firms to receive a PPP loan. Larger firms (as measured by revenues and the number of full-time employees and owners), older firms, and firms with younger owners are more likely to receive PPP loans. Adding these controls reduces the estimated disparity in PPP take-up for Black-owned firms as they are smaller, younger, and located in ZIP codes with lower bank branch density.

The estimated unconditional and conditional disparities in PPP take-up are nearly identical to the estimates in Chernenko and Scharfstein (2023), who use data on PPP take-up by the population of Florida restaurants. They find unconditional disparities for Black and Hispanic firms of 25.5 and 10.7 percentage points, compared to our estimates of 25.7 and 8.4 percentage points.[25] Controlling for a different set of observable characteristics, Chernenko and Scharfstein (2023) estimate conditional disparities for Black and Hispanic firms of 9.2 and 5.7 percentage points, compared to our estimates of 8.9 and 6.1 percentage points.[26] The similarity in results between the two papers using very different samples help validate the accuracy of survey responses and mitigates any concerns about sample selection and representativeness of the SBCS sample.

In columns 3–6 of Table 2, we report the results of linear probability models in which the dependent variable is an indicator variable equal to one if a firm receives a PPP loan from a bank and zero if it receives a PPP loan from another source: a fintech, a credit union, or a CDFI.[27]

[25] They also find a 4.8 percentage points disparity for female-owned owned, compared to our estimate of 5.4 percentage points. Where the two papers differ is in the estimates of unconditional disparities for Asian-owned firms. Chernenko and Scharfstein (2023) find a negative 2.3 percentage points disparity, weakly statistically significant at 10%, while we find a positive 5.5 percentage points disparity. This difference could be due to sample selection: Asian-owned firms make up almost 12% of their sample but only 6% of the 2020 SBCS.

[26] Chernenko and Scharfstein (2023) estimate statistically insignificant disparities for Asian- and female-owned firms. We estimate an insignificant disparity for Asian-owned firms and a positive and statistically significant disparity of 2.9 percentage points for female-owned firms.

[27] The estimates are similar if we exclude credit unions and CDFIs from the sample.

Firms that do not receive a PPP loan are excluded from the sample. When the only regressors are indicator variables for race/ethnicity and gender (column 3), we find that Black-owned PPP recipients are 14.2 percentage points less likely than white-owned businesses to receive their PPP loans from a bank, and this differential is highly statistically significant. Hispanic-owned firms are 3.3 percentage points less likely to receive their PPP loan from a bank, but the differential is only weakly significant. There is no statistically significant difference for Asian-owned firms, while female-owned firms are 5.1% less likely to receive a bank loan, and this difference is statistically significant.

The fourth column of Table 2 adds the full set of controls and fixed effects. Including these controls reduces the estimated differential in bank PPP borrowing for Black-owned firms to 9.2 percentage points, but it remains highly significant. Larger firms, older firms, firms with older owners, and those located in ZIP codes with more bank branches per capita are more likely to get PPP funding from banks. As in column 2, the inclusion of these controls reduces the estimated differential between white-owned firms and Black-owned firms due to the negative in-sample correlation of these characteristics with Black business ownership. Including controls also reduces the differential in bank PPP take-up for Hispanic-owned firms to a statistically insignificant level. Female-owned firms remain significantly less likely to get their PPP funding from banks, although this estimate is reduced to 1.9 percentage points.

The remaining columns of Table 2 examine whether Black-owned PPP recipients located in more racially biased counties are less likely to receive their PPP loans from banks. We use the explicit and implicit bias measures from Project Implicit. In column 5, we add an interaction of the Black-ownership indicator with the explicit bias measure. The coefficient of the interaction term is negative and statistically significant, implying that Black-owned firms in more racially biased counties are less likely than other Black-owned firms to receive PPP loans from banks. The coefficient implies that Black-owned firms in counties with explicit bias one standard deviation above the nationwide mean are 11.4 percentage points less likely to receive their PPP loans from banks relative to observably similar Black-owned firms in counties with average explicit bias. Overall, Black-owned firms in counties with explicit bias one standard deviation above the nationwide mean are 20.6 percentage points less likely than observably similar white-owned firms in those same counties to receive their PPP loans from banks. The findings for the implicit bias measure are similar in magnitude, as reported in column 6 of the table.[28]

[28] We also examined a measure of racial bias based on the 2019 Nationscape Survey, which is similar to the explicit bias measure. While the estimated effects of the Nationscape racial bias measure are statistically significant, they are much smaller in magnitude than the estimated effects of the Project Implicit bias measures. This is likely because the Nationscape measure covers a much larger population than a county, probably with a much wider variation in racial attitudes. Thus, even though the explicit bias measure and the Nationscape measure are similar, there is likely to be more measurement error in the Nationscape measure of the bias that actually affects Black-owned firms, which would shrink the estimates towards zero.

Taken together, these findings are consistent with prior research showing that Black-owned firms are less likely to receive PPP funding from banks and that racial bias may play a role in explaining this fact. What is less clear is the mechanism that drives these empirical findings. In particular, is there a disparity in PPP take-up because Black-owned firms are less likely to apply for PPP loans or because their applications are less likely to be approved? Likewise, do Black-owned firms rely more on fintech lenders because they are more likely to apply to fintechs or because fintech lenders are more likely than banks to approve their applications? Finally, does the lower take-up of bank PPP loans by Black-owned firms in more racially biased counties stem from their lower application rates to banks in these counties or from greater disparities in bank approval rates in those counties? We use our survey data to address these questions, considering in turn applications and then approvals.

4.2 Applications: Who Applies?

Table 3 examines disparities in PPP applications by estimating linear probability model regressions of whether a firm applies for a PPP loan. In column 1, the only explanatory variables included are indicator variables for race, ethnicity, and gender. We find that Black-, Hispanic- and female-owned firms are, respectively, 19.4, 5.7, and 5.2 percentage points less likely to apply for PPP, while Asian-owned firms are 4.9 percentage points more likely to apply for PPP than white-owned firms. Adding firm, owner and location controls substantially reduces the application differentials, particularly for Black-owned firms. With controls, Black-owned firms are 4.9 percentage points less likely to apply for PPP loans. This finding allows us to conclude that the disparity in PPP application rates explains a substantial share of the PPP take-up disparity between observably similar white- and Black-owned firms, which is estimated to be 8.9 percentage points (see column 2 of Table 2).[29]

What factors cause this disparity in application rates between observably similar white- and Black-owned firms? Columns 3 and 4 of Table 3 examine the role of racial bias. We include the same set of controls and fixed effects as in column 2 of the table but now interact the Black-owned indicator variable with our county-level measures of explicit and implicit racial bias. The coefficient estimates of the interaction terms in columns 1–2 are small and statistically insignificant, indicating that Black-owned firms are not less likely to apply for PPP loans in more racially biased counties relative to counties that are less racially biased.

In column 5 of Table 3, we investigate whether application disparities are in part due to racial

[29] Note that this is only a statistical claim. It does not answer the question of what the take-up disparity would have been had more Black-owned firms applied for PPP loans. Black-owned firms that did not apply for PPP may have been less likely to be approved than observably similar Black-owned firms that did apply.

disparities in the likelihood of having a relationship with a bank.[30] Chernenko and Scharfstein (2023) and Howell et al. (2024) show that firms with outstanding bank loans are more likely to receive PPP loans but that controlling for these prior relationships does not have a material impact on the measured disparities in PPP lending. These findings are consistent with press accounts indicating that banks prioritized existing customers when accepting applications. Thus, it is possible that our estimated application disparities reflect the fact that Black-owned businesses were less likely to have pre-existing bank relationships. Unfortunately, the 2020 survey only collects information on pre-pandemic lender relationships among firms that applied for PPP. The survey does, however, have information on whether the firm had a bank relationship at the time of the survey (fielded in September and October of 2020). In column 5, we find that firms with current bank relationships are 11.3 percentage points more likely to apply for PPP funding, and that controlling for current bank relationships reduces the estimated application disparity between Black- and white-owned firms from 4.9 percentage points to 3.8 percentage points. However, the estimated effect of current bank relationships on applications is likely stronger than it would be if we had used data on pre-pandemic bank relationships, given that receipt of a PPP loan may have created a new bank relationship that was later reported by survey respondents. Since this measure of bank relationships may proxy for receipt of a PPP loan, and Black- and Hispanic-owned firms are less likely to receive PPP loans, including this variable likely biases the coefficients of *Black* towards zero.[31]

To further investigate the sources of application disparities, we next analyze responses to a survey question asking PPP non-applicants why they did not apply. Importantly, respondents could select as many suitable reasons as they wished. In Table 4, we estimate linear probability model regressions of seven possible reasons that respondents were able to cite for not applying for PPP. All regressions in the table incorporate our full set of firm and ZIP code controls, as well state and industry fixed effects. In columns 1 and 2 of the table, we show that Black-owned firms do not have lower demand for PPP funding, indicating that lower demand cannot explain the disparity in application rates. Specifically, column 1 shows that Black-owned firms that did not apply for PPP loans are 7.4 percentage points less likely than observably similar white-owned firms to say they did not apply because they did not need the funding. Column 2 shows that Black-owned firms are also 2.1 percentage points less likely to cite a lack of interest in government aid.

Columns 3 and 4 of Table 4 suggest that differential concerns about program eligibility were likewise not an important driver of the application disparity. In column 3, we find that Black-owned firms are no more or less likely than white-owned firms to say they did not apply for PPP loans

[30] Li and Strahan (2021) and Balyuk, Prabhala, and Puri (2021) study the role of bank relationships in access to PPP but do not investigate whether these may explain racial disparities.

[31] In Internet Appendix Table IA5, we show that controlling for primary business owners' personal credit score (at the time of the survey) does not change the estimated application disparity.

out of concern that they would not qualify either for the loan or for loan forgiveness. In column 4, we find that Black-owned firms are no more or less likely than white-owned firms to say they did not apply because they could not find a lender to accept their application. If Black-owned firms were less likely to qualify for a PPP loan, they may have been more likely to be turned away by prospective lenders concerned about complying with program rules.

Columns 5–7 of Table 4 indicate that the "administrative burdens" of the PPP may have been an important cause of disparities in application rates. Broadly speaking, the term "administrative burdens" refers to the time and effort costs a firm incurs to apply for a PPP loan. For instance, firms need to gather and synthesize enough information about the program to fully understand and assess the program's benefits and risks. Firms also need to collect, organize, and prepare all documents required to submit an application. In the Appendix, we describe the documentation required to apply for PPP loans and the calculations needed to determine the loan amount for which the firm is eligible. As the description in the Appendix makes clear, the documentation requirements and loan amount calculations are quite intricate, creating administrative burdens that may dissuade some business owners from applying for PPP loans.

In column 5, we report that Black-owned firms that did not apply for PPP loans are 5.8 percentage points more likely than observably similar white-owned firms to say they did not apply because the "program/process was too confusing." This finding supports the view that Black-owned firms either had less support in preparing PPP loan applications or faced a more complex set of issues in filling out their applications. The regression reported in column 6 shows that Black-owned firms are 4.7 percentage points more likely to say they did not apply for a PPP loan because they were unaware of the program, suggesting that Black-owned firms may have had less access to people who were familiar with the program, such as other business owners, bankers, accountants or lawyers. Finally, column 7 of the table finds that Black-owned firms are 7.4 percentage points more likely not to apply for a PPP loan because they missed the program deadline. Among other possibilities, missing the deadline could be related to difficulties in gathering information about the program or preparing the application. Collectively, the results in columns 5–7 suggest that the administrative burdens of the program may have been experienced more acutely by Black-owned firms, which may partly explain the observed disparity in application rates.

Why might the administrative burdens of the PPP have had a greater effect on the decision of Black-owned firms to apply for PPP loans? First, Black-owned firms may be more likely to have attributes that increased the complexity of their PPP applications. For example, according to Table 1, Black-owned firms are significantly more likely to use contract workers, whose compensation was not supposed to be included in the calculation of the eligible loan amount. This was a source of confusion for many companies. While we control for use of contract workers in the regressions in Table 3, there could be other unobserved characteristics of Black-owned firms that made it more difficult to determine the eligible loan amount or provide the required documentation. Second, Black-owned firms tend to have weaker bank relationships and may therefore be less likely to receive help from bank loan officers in preparing PPP applications.[32] Finally, Black-owned firms may have had less access to other business owners and professionals, such as accountants and lawyers, to assist them in preparing their PPP applications. Indeed, evidence from the 2021 Small Business Credit Survey indicates that Black-owned firms have less access to professional services. On average, 64% of white-owned employer firms indicate that they turn to paid professional services (such as accountants, lawyers, or consultants) when faced with a business-related problem, relative to just 42% of Black-owned firms.[33] This differential is explained in part by firm characteristics such as size and profitability, but even when including these controls in a regression analysis, Black-owned firms are still over 9 percentage points less likely to use paid professional services. Evidence from the American Survey of Entrepreneurs conducted by the U.S. Census corroborates this differential: 68% of white-owned employer firms seeking business-related advice turned to legal or professional advisors, relative to just 58% Black-owned employer firms.[34] In addition, consistent with a lower level of support from paid professional advisors, Black-owned employer firms were substantially more reliant on government-supported technical assistance programs, such as SBA Small Business Development Centers, with 10.3% utilizing these resources relative to just 2.8% of white-owned employer firms.[35]

4.3 Applications: Where do Firms Apply?

We next study the factors that affect whether a firm applies for a PPP loan from a bank or fintech. In columns 1–2 of Table 5, we estimate linear probability regression models of whether a firm applies for a PPP loan from a bank, conditional on submitting a PPP loan application. We find that Black-owned firms are 16.5 percentage points less likely than white-owned firms to apply to banks (column 1). After including our full set of controls, this disparity shrinks to 9.9 percentage points (column 2). By contrast, conditional on applying for a PPP loan, Black-owned firms are 14.7 percentage points more likely to apply to fintechs (column 6). Controlling for observable characteristics reduces this estimate to 7.8 percentage points (column 7).

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[32] According to the 2020 Small Business Credit Survey, minority-owned firms were significantly less satisfied than white-owned firms with the support that they received from their primary financial services provider.

[33] Federal Reserve Member Banks, 2022 Report on Employer Firms: Data Appendix, February 22, 2022, at https://www.fedsmallbusiness.org/-/media/project/smallbizcredittenant/fedsmallbusinesssite/fedsmallbusiness/files/2021/sbcs-employer-firms-appendix-2021.xls?sc_lang=en&hash=2A3C7FEFDF3E623AF175ADA8E2822A14

[34] US Census, ASE: Characteristics of Businesses: 2016 Tables, at https://www.census.gov/data/tables/2016/econ/ase/2016-ase-characteristics-of-businesses.html

[35] *Ibid.*

The coefficients on various firm characteristics in Table 5 demonstrate that firms with fewer resources are particularly likely to apply to fintechs rather than banks. Businesses that are smaller, younger, and have lower annual revenues are more likely to apply to fintechs. One interpretation of this finding is that these types of firms benefit most from the simpler, streamlined application processes that fintechs offered. To the extent that our controls are unable to fully capture differences between Black-and white-owned firms in access to informational and technical resources, this mechanism may help to explain why observably similar white- and Black-owned firms display different preferences for banks and fintechs. Indeed, the evidence in the last 3 columns of Table 4, suggesting disparities in the administrative burdens of the PPP even after controlling for observable characteristics, is consistent with the idea that Black-owned firms prefer fintechs because of their streamlined application processes.

Does racial bias help to explain why Black-owned firms appear to prefer fintechs to banks? In columns 3–4 and 8–9 of Table 5, we interact our measures of county-level racial bias with the indicator for Black-owned firms. Columns 3 and 4 show that in more racially biased counties, Black-owned PPP applicants are less likely to apply for PPP loans from banks. In particular, the coefficient estimate for the explicit bias measure indicates that Black-owned businesses in counties with racial bias one standard deviation above the nationwide mean are 9.5 percentage points less likely to apply for PPP loans from banks relative to observably similar Black-owned businesses in counties with an average level of racial bias. Compared to white-owned firms, Black-owned firms are 19.3 percentage points less likely to apply for bank PPP loans in counties one standard deviation above the nationwide mean of explicit racial bias. The estimated effects using the implicit bias measure are very similar in magnitude. In columns 8 and 9, the regression results indicate that Black-owned firms in more racially biased counties are more likely to apply for PPP loans from fintechs. The coefficient estimates are large (0.071 for the explicit bias measure and 0.099 for the implicit bias measure), implying that in more racially biased counties, the greater application rates by Black-owned firms to fintechs offset a large portion of the lower application rates for PPP loans from banks.

Why might racial bias lead Black-owned firms to apply to fintechs? One possibility is that Black-owned firms located in racially biased areas anticipated — perhaps based on a legacy of racial discrimination by banks — that they would receive discriminatory treatment if they submitted their PPP applications to banks, choosing instead to submit to fintechs. Another explanation is that Black-owned firms in more racially biased areas were equally likely to approach banks to inquire about submitting a PPP application, but chose to submit to a fintech after being treated poorly by bank loan officers. It is also possible that Black-owned firms in more racially biased areas differ systematically from other Black-owned firms along unobservable dimensions that would strengthen their preference for fintechs relative to banks. For instance, as a result of past discrimination, Black-owned firms in more biased areas may have less access to resources to assist them in preparing PPP applications. As a result, these firms may place a higher value on the ability of fintechs to streamline the application submission process.

Finally, in columns 5 and 10 of Table 5, we ask whether existing bank relationships could drive the decision to apply to banks versus fintechs. We find that, while firms with current bank relationships are 27.3 percentage points more likely to apply to banks and 8.5 percentage points less likely to apply to fintechs, this variable has only a modest effect on whether Black-owned firms apply to banks or fintechs. Conditional on applying for a PPP loan, Black-owned firms are still 8.5 percentage points less likely to apply to banks and 7.5 percentage points more likely to apply to fintechs.[36]

In sum, the findings in Tables 3-5 demonstrate that application behavior explains a large portion of the findings that: (i) Black-owned businesses are less likely to receive PPP loans (Chernenko and Scharfstein, 2023); (ii) conditional on receiving PPP loans, Black-owned businesses are less likely to have used banks and more likely to have used fintechs (Howell et al., 2024); and (iii) the reliance of Black-owned firms on fintechs, relative to banks, is especially pronounced in more racially biased counties. The importance of observable differences between Black- and white-owned firm in explaining application behavior suggests that Black-owned businesses may have had fewer resources to help navigate the administrative burdens associated with PPP applications. Importantly, we note that observable differences between white- and Black-owned firms, as well as the possibility that administrative burdens had a particularly strong effect on Black-owned firms, may themselves be outcomes of historical discrimination.

4.4 Approvals

We next examine the determinants of PPP loan approvals. As noted above, an "approval" by a particular lender type refers to an applicant who receives a PPP loan from that lender type. If an applicant does not receive a PPP loan from a given lender type, it does not mean that the loan application was explicitly rejected, as it is possible that the application was withdrawn or never attended to, or that the applicant was approved by a different lender type.

Table 6 reports the results of linear probability model regressions of loan approvals. Columns 1 and 3, respectively, show that banks and fintechs are 11.6 and 15.4 percentage points less likely to approve applications from Black-owned firms relative to white-owned firms. We include our full set of controls in columns 2 and 4 and find that the approval disparity between observably

[36] The sample analyzed in Tables 3 and 5 excludes 292 firms that do not report the outcome of their PPP application, while including those that report that they have a current bank relationship. Internet Appendix Table IA1 shows that the pattern of coefficients and their statistical significance does not depend on the inclusion or exclusion of these firms.

similar white- and Black-owned firms is 7.4 percentage points at banks and 8.4 percentage points at fintechs.[37] The difference in approval disparities between banks and fintechs documented in columns 2 and 4 is not statistically significant.[38] Thus, the greater take-up rate of fintech PPP loans by Black-owned firms is not because the disparity in approval rates is lower at fintechs; rather, it is driven by the greater likelihood that Black-owned firms apply to fintechs, as shown in Table 5.

The large differences between unconditional (columns 1 and 3) and conditional (columns 2 and 4) approval disparities are noteworthy for several reasons. In principle, PPP approval is a deterministic function of eligibility: under the program's rules and according to issued SBA guidance, all eligible applications should be approved. By this logic, observable firm characteristics should explain approval outcomes only insofar as they explain eligibility rates, and disparities estimated conditional on these characteristics should reflect to a lesser degree the impact of any racial differences in eligibility rates among PPP applicants. Thus, by including our full set of firm controls, we help to assuage concerns that the estimated disparities in columns 1 and 3 are driven by unobserved disparities in eligibility rates between white- and Black-owned applicants.[39] The differences between unconditional and conditional disparities also provide an intuitive measure of disparate impact in the approval process: our results indicate that differences between white- and Black-owned firms on other observable dimensions, in particular with respect to firm revenues, size and age, are able to explain almost half of the unconditional disparities in approval rates at both banks and fintechs. More generally, the fact that firm characteristics have strong explanatory power for approval outcomes indicates that the PPP approval process is *not*, in practice, a deterministic function of eligibility. In column 6, which pools applicants to all lender types, the estimated signs and magnitudes on firm characteristics demonstrate that firms with more resources (larger, older, higher revenues) are significantly more successful in obtaining approval. As we argue in section 5.3, under-resourced firms are least likely to navigate the administrative burdens of getting approved for PPP loans.

Table 7 explores whether racial bias affects approval rates. We continue to include all controls,

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[37] Because the vast majority of bank PPP applicants in the survey, about 90%, report having pre-existing relationships with their bank, we stress that the lack of significance on "Relationship w/Lender" should not be interpreted as evidence that pre-existing bank relationships had no effect on PPP access.

[38] In Table IA3, we show that our results are robust to controlling for whether firms submit PPP applications to multiple lender types, which indicates that neither the bank nor the fintech approval disparity are likely to be driven by Black-owned firms being particularly likely to be approved by one lender type while waiting to hear back from a different lender type. In Table IA4, we show that the results in columns 3–4 are robust to considering applications only to fintech lenders as a rejection by a bank.

[39] For example, there was widespread concern in the first round of PPP about nonemployer firms reporting zero or negative profits in 2019 being de-facto ineligible (i.e., their maximum eligible loan amounts were zero); we control for employer/nonemployer × profitability, effectively partitioning out the set of nonemployer firms with zero or negative profits in 2019. In untabulated results, we also re-estimate these regressions without these firms included in the sample and obtain very similar estimates.

but to conserve space report only the coefficients on *Black* and its interactions with explicit and implicit bias. We find that Black-owned firms applying to banks are significantly less likely to be approved in more racially biased counties. The results reported in column 1 indicate that the estimated approval disparity for Black-owned applicants in counties one standard deviation above the nationwide mean of explicit bias is 7.6 percentage points greater than in counties with average racial bias. In these more racially biased counties, Black-owned applicants are 15 percentage points less likely to be approved for a bank PPP loan relative to observably similar white-owned applicants. Conversely, the results in column 1 indicate that there is no approval disparity in counties one standard deviation below the nationwide mean of explicit bias. Column 2 reports similar estimates using the implicit bias measure. The results are again statistically and economically significant.

Columns 3 and 4 examine the effect of racial bias on differential approval rates at fintechs. The coefficient estimates indicate that the approval disparity is lower in more racially biased counties, thereby offsetting the higher approval disparity by banks in these counties. This may be because the lower bank approval rate in more racially biased counties drive Black-owned applicants with favorable unobservable characteristics to fintechs, which then approve their applications at higher rates. The magnitude of the effect is large; however, because of the much smaller number of fintech applications, it is measured with considerable noise and the point estimates are not statistically significant. Finally, columns 5 and 6 examine the effect of racial bias on approval disparities across all lenders. The point estimates for the racial bias interaction terms are negative, but not statistically significant, reflecting offsetting effects of bias on bank and fintech approval disparities.

While the results in Table 6 show similar observed approval disparities at banks and fintechs — and thus cannot explain the greater reliance of Black-owned firms on fintechs — this does not necessarily imply that approval disparities at banks and fintechs would be the same for randomly selected white- and Black-owned businesses. Indeed, our discussion in the prior section suggests that fintechs may increase credit access by expanding the PPP applicant pool to include firms with fewer resources, who in turn could face lower probabilities of approval. Black-owned firms may be particularly well-represented in this group of new applicants. However, a more careful consideration of the application decisions of Black- and white-owned firms suggest that, if anything, selection *reduces* observed fintech disparities relative to observed bank disparities. That is, we would expect fintech disparities to be even larger relative to bank disparities with random assignment of firms to lender types.

In the appendix, we present a model that elucidates how endogenous application behavior affects relative approval disparities at banks and fintechs. Our model can jointly rationalize racial disparities in the propensity to apply for PPP, in choice of lender type, and in overall rates of approval (that is, across all lender types). However, the model cannot additionally generate similar approval disparities between banks and fintechs, and there does not exist *any* set of parameters under which the model can generate a larger approval disparity at fintechs than at banks. The model fails on this dimension precisely because the two key selection effects present in our setting both *reduce* approval disparities at fintechs relative to banks: one tends to decrease the fintech applications of Black-owned firms that have the lowest likelihood of being approved; the other tends to increase fintech applications from Black-owned firms that have a relatively high likelihood of being approved. These selection effects emerge in a model with the following features: (i) firms prefer bank PPP loans to fintech PPP loans because there are greater expected future benefits of having a bank relationship; (ii) the cost of applying to fintechs is lower than the cost of applying to banks; (iii) banks discriminate against Black applicants, who thus have a lower probability of being approved at a bank than at a fintech; (iv) the distribution of PPP approval probabilities, θ, among the population of Black-owned firms is a leftward shift of the analogous distribution for white-owned firms. This downward shift is not a direct result of racial bias in the PPP application process, but it could be the result of Black-owned firms having fewer resources to assist in applying for PPP loans.

Under these assumptions, low-θ firms apply to fintechs while high-θ firms apply to banks, as the higher approval probability makes it more worthwhile to bear the higher bank application costs. If application costs are low, leading all firms to apply for PPP loans, and there is no discrimination at banks, then the approval disparities would be the same at banks and fintechs, reflecting the assumption that the distribution of θ for Black-owned firms is a leftward shift of the distribution of θ for white-owned firms. However, given this leftward shift and meaningful application costs, the cost of applying to a fintech crowds out a larger fraction of low-θ Black-owned firms, thus increasing the average θ of Black-owned firms that apply to fintechs relative to the average θ of white-owned firms that apply to fintechs. This censoring effect thus reduces the approval disparity at fintechs but has no effect on the approval disparity at banks.

In addition, discrimination leads more Black-owned firms in the middle of the θ distribution to apply to fintechs; only the very highest θ Black-owned firms will apply to banks in the hope of benefiting from the future value of a bank relationship. This increases the average θ of Black-owned fintech loan applicants relative to white-owned fintech loan applicants. And while the average θ of Black-owned firms applying to banks also increases, the effect of this selection on the approval probability of Black-owned firms at banks is smaller than it is at fintechs because of discrimination at banks. Thus, selection effects arising from discrimination also reduce the approval disparity at fintechs relative to banks. In summary, our model clarifies that selection effects should, in theory, lead to a smaller approval disparity at fintechs relative to banks.

Our empirical finding that PPP approval disparities are roughly equal at banks and fintechs suggests that either selection effects are weak or that there is another cause of PPP approval disparities that is particularly acute at fintechs. In the next section, we will explore other possible sources of racial disparities in PPP approval rates.

5 Understanding Approval Disparities

Even though fintechs appear to have reduced the impact of racial bias on PPP approval decisions (Table 7), we find similarly large average approval disparities at both banks and fintechs (Table 6). This suggests that there are additional reasons, beyond those we have already analyzed, for racial disparities in PPP approval rates. In this section, we investigate several other factors that may have contributed to average approval disparities at banks and fintechs. The first potential explanation is that while lenders were equally likely to approve applications from Black-owned firms, these firms were less likely to accept loan offers. The second potential explanation is that despite our rich controls for firm, owner, and location characteristics, there may be unobserved characteristics of Black-owned businesses that reduced their likelihood of meeting PPP eligibility requirements. The third possibility is that, as we argue in the context of the decision to apply for a PPP loan, the administrative burden of the PPP had a bigger impact on Black-owned firms. In other words, Black-owned firms may have been equally likely to be eligible for PPP loans but less likely to be able prove that they were eligible — or prove that they were eligible for the amount they requested — because of either inadequate documentation or because they requested more than the amount for which they were eligible. We consider each explanation in turn.

5.1 Potential Explanation 1: Turning down Approved Funds

On its face, the idea that Black-owned firms are more likely to turn down loan offers is implausible both because of the attractive terms of the forgivable loan and the fact that the firms applied for the loan in the first place.[40] It is also inconsistent with our evidence regarding the reasons that PPP non-applicants cited for their decision not to apply. Recall from the regression in column 1 of Table 4 that Black-owned firms are 7.4 percentage points less likely than observably similar white-owned firms to state that they did not apply because they did not need funding. Moreover, column 2 of the same table shows that Black-owned firms are less likely to state that they did not apply for a loan because they were not interested in government funding. We would expect Black-owned firms to be more likely to state these reasons if they were more likely to turn down

[40] Balyuk, Prabhala, and Puri (2021) provide evidence of "funding hesitancy" among small publicly-traded firms. Following negative media coverage and Treasury Secretary Mnuchin's announcement that firms receiving loans of more than $2 million will be closely scrutinized, about 17% of publicly-traded returned their PPP loans. Concerns about potential ex-post government scrutiny are unlikely to apply to all but perhaps a handful of firms in our sample, as they are at least an order of magnitude smaller than the publicly-traded firms in the Balyuk, Prabhala, and Puri (2021) sample. The mean of the number of owners and employees in our sample is nine, versus more than two hundred in the sample of publicly-traded firms studied by Balyuk, Prabhala, and Puri (2021), and fewer than 3% of firms in our sample have more than 50 employees. Firms returning PPP loans are even larger: the mean firm has 390 employees and receives a PPP loan of $4.43 million. Finally, only 4% of PPP recipients in our sample report receiving a loan of at least $2 million, and among Black-owned PPP recipients this fraction falls to 3%.

PPP funds for which they had already been approved.

5.2 Potential Explanation 2: Eligibility

Because the approval regressions include detailed firm and owner characteristics, any eligibility disparity between Black- and white-owned firms must be based on differences in some unmeasured characteristics of either firms or their owners. The main reasons an applicant would be ineligible, as noted explicitly on the PPP application, are the following: (i) the applicant is currently involved in a bankruptcy; (ii) the applicant is currently delinquent on a federal loan or has defaulted on a federal loan in the last seven years; (iii) an owner with more than 20% of the equity is either currently facing criminal charges, on probation, or incarcerated; (iv) an owner with more than 20% of the equity was convicted of a felony, pleaded guilty to a felony, or was on probation for a felony in the last five years. We consider bankruptcy, delinquency or default on a federal loan, and criminal records in turn, and we conclude that these eligibility issues cannot explain a meaningful portion of the approval disparity at banks and fintechs.

(i) Bankruptcy: The SBA released guidance in April of 2021 clarifying the meaning of the phrase "presently involved in any bankruptcy" as used on SBA Form 2483.[41]. In the first two quarters of 2020, a total of just under 400,000 personal and business bankruptcies were filed (Iverson et al., 2020), almost all of which were personal bankruptcies. This represents less than 0.2% of the U.S. adult population. While Black Americans have filed for bankruptcy at higher rates than white Americans in recent years,[42] the disparity in filing rates is not large enough to explain a material fraction of the observed 8 percentage points approval disparity.

(ii) Federal Loan Default/Delinquency: The federal government uses two databases to screen for histories of federal loan defaults and delinquencies: the Credit Alert Interactive Verification Reporting System (CAIVRS) and the Treasury Offset Program debtor database (TOP). The CAIVRS database is composed of people who have defaulted on debt either guaranteed or issued by six participating federal agencies: Housing and Urban Development, Veterans Affairs, Small Business Administration, Education, Agriculture, and Justice. The TOP database includes people delinquent on non-tax federal debt (e.g., child support).

Federal agencies, including the SBA, are able to access both CAIVRS and TOP through the Treasury's Do Not Pay (DNP) portal. However, the SBA did not perform any such pre-origination

[41] SBA, Paycheck Protection Program Loans Frequently Asked Questions (FAQs), Question 67, April 6, 2021, at https://www.sba.gov/sites/default/files/2021-04/PPP%20FAQs%204.6.21%20FINAL-508.pdf.

[42] Paul Kiel and Hannah Fresques, Data Analysis: Bankruptcy and Race in America, September 27, 2017, at https://projects.propublica.org/graphics/bankruptcy-data-analysis.

checks in 2020, although it did do so in 2021 prior to authorizing loans.[43] Because only federal agencies have access to the DNP portal and the only way of accessing the TOP debtor database is through the DNP portal,[44] we therefore know that no PPP applicants were rejected for PPP loans in 2020 due to being in TOP.

Unlike TOP, CAIVRS also provides direct access to private lenders approved to make federally-guaranteed loans on behalf of one of the participating agencies. So while the SBA may not have run CAIVRS checks on PPP applicants in 2020, PPP lenders may have done so. Fortunately, HUD releases monthly statistical reports on the volume of direct CAIVRS inquiries received from approved lenders and the number of matches found in the CAIVRS database, categorized by the participating agency to which lenders submitted requests.[45] The reports suggest that some lenders did perform CAIVRS checks on PPP applicants in 2020: the volume of requests submitted on behalf of the SBA increased from just under 20,000 in March of 2020 to more than 250,000 in April of 2020.[46] However, a total of just 481,680 requests were submitted on behalf of the SBA between April and August of 2020, representing under 10% of approved PPP loans. Of these requests, just 3,656 returned matches, less than 0.1% of approved loans during this period. Because default and delinquency rates in the population are much higher than the default and delinquency rate implied by this number, the data suggest that small business owners who had defaulted or were delinquent chose not to apply for PPP loans. Given the low percentage estimated above, we can rule out the possibility that there are meaningful disparities in PPP approvals in 2020 due to applicant defaults or delinquencies on federally-backed loans.

(iii) - (iv) Criminal Record: Using data from the Criminal Justice Administrative Records System, Finlay, Mueller-Smith, and Street (2020) estimate that, under the original program rules, Black male (female) sole proprietors were 3.6 percentage points (1.4 percentage points) more likely than white male (female) sole proprietors to be ineligible for PPP because they had a criminal record. Given that about 55% of Black-owned firms in our sample are female-owned, the average disparity in criminal record-related disqualification for sole proprietors in our data is estimated to be around 2.4 percentage point ($= 0.036 * 0.45 + 0.014 * 0.55$).

[43] US GAO Report 21-577 to Congressional Addressees, Paycheck Protection Program: SBA Added Program Safeguards, but Additional Actions Are Needed, July, 2021, page 16, at https://www.gao.gov/assets/gao-21-577.pdf.

[44] Treasury Offset Program (Debt Check) Do Not Pay (DNP) Quick Reference Card, at https://www.fiscal.treasury.gov/files/dnp/qrc-top-debt-check.pdf.

[45] U.S. Department of Housing and Urban Development, CAIVRS Monthly Report Request, at https://entp.hud.gov/caivrs/public/f57pdf-main.cfm.

[46] For example, Lendistry, a minority-led CDFI, appears to have run CAIVRS checks on their applicants in 2020. See: PIDC, PPP Application Guidelines & Submissions with Lendistry, April 24-26, 2020, at https://web.archive.org/web/20221114190914/https://pidcphilablog.com/wp-content/uploads/2020/04/PIDC-webinar-PPP-Lendistry.pdf.

Disqualification rates based on criminal records are likely lower for owners of employer firms than for sole proprietors. Adamson et al. (2021) study the broader small business population but with a narrower focus on felony convictions in the past five years, finding that about 0.47% of small businesses were ineligible due to prior felony convictions under the original PPP rule. This 0.47% rate of felony convictions in the past five years is substantially lower than the 1.2% rate in the sample of sole proprietors studied in Finlay, Mueller-Smith, and Street (2020) and may reflect the various barriers, including access to credit, that business owners with criminal records face in growing their businesses. To estimate the overall disparity in criminal record-related disqualification among all small businesses, we therefore multiply the 2.4% estimate above by the ratio of conviction rates (0.47%/1.2%) to get 0.94%.

In addition to this evidence, our prior results from the sample of PPP non-applicants also indicate that eligibility was not a disproportionately strong concern for Black-owned businesses. In column 3 of Table 4, we show that Black-owned firms were no more likely than observably similar white-owned firms to say they did not apply for PPP due to concerns about being eligible for either the loan or for loan forgiveness. Of course, since the sample in Table 4 consists of firms that did not apply, we cannot rule out the possibility that ineligible Black-owned firms were more likely to apply than ineligible white-owned firms. However, the fact that column 4 show that Black-owned firms were no more likely to cite difficulty finding a lender to accept their PPP application cuts against this possibility, as lenders would presumably be less likely to accept applications on behalf of ineligible firms. Thus, eligibility issues would seem to explain only a very small part of the disparity in approval rates.

5.3 Potential Explanation 3: Administrative Burden

As we discussed in Section 4, the administrative burdens of the PPP — which include documenting program eligibility and substantiating a loan request — likely fell more heavily on under-resourced firms, whose applications were less likely to be approved given their documentation deficiencies.[47] This is consistent with our findings in Section 4.4 that smaller and younger firms — those prone to having fewer resources to complete a fully documented and substantiated application — were less likely to have their applications approved. It is also consistent with anecdotal evidence suggesting that small firms faced more challenges preparing a fully documented and substantiated

[47] Greater Phoenix Economic Council, Five Tips for PPP Applicants, April 22, 2020, at https://www.gpec.org/blog/5-tips-federal-loan-applicants/; Fiserv Support for SBA Paycheck Protection Program (PPP) Frequently Asked Questions, April 21, 2020, at http://contentz.mkt3120.com/lp/46886/732931/SBA%20Paycheck%20Protection%20Program%20Support%20FAQ_1.pdf; Megan Leonhardt, Here's How to Avoid a Common Mistake Small Businesses Make when Applying for Loans, According to an SBA Official, April 22, 2020, at https://www.cnbc.com/2020/04/22/common-mistake-small-businesses-make-applying-for-loans-says-sba-official.html.

application. Jared Hecht, the CEO of Fundera, an online marketplace that connects small business owners with lenders, stated that "approximately 75% of [PPP] applications [Fundera processes] need some form of correction, whether it's a missing piece of documentation, the wrong document, an incorrect payroll calculation, or otherwise."[48] Peapack-Gladstone Bank, a New Jersey bank which had close to $6 billion in assets in March 2020, released a report describing their PPP lending experience in which they stated that "smaller enterprises, such as local retailers and restaurants and the like, presented rudimentary documentation." According to Peapack-Gladstone executive Stuart Vorcheimer, "some of our clients literally were providing us with payroll numbers handwritten on a piece of paper."[49]

Like small and young firms, Black-owned firms are more likely to be under-resourced and thus to face greater challenges navigating the PPP application process. This could help explain approval disparities between observably similar Black- and white-owned firms. Indeed, as we discussed in Section 4.2, Black-owned firms are less likely than white-owned firms to have access to paid professional services such as legal and accounting services. This disparity in professional services access exists even when controlling for firm size and firm age. There is considerable anecdotal evidence to support this explanation of approval disparities, as noted in congressional testimony, policy proposals, press interviews and other accounts.[50] As further support for this explanation, we note that numerous organizations developed programs to help Black-owned businesses submit PPP applications, which suggests that Black-owned businesses faced greater application challenges. Paybby, which describes itself as "a consumer finance technology company seeking to offer black and brown communities what they truly need—a bank offering more targeted services [and] financial empowerment through education..." launched an initiative in January of 2021 called "Together We

[48] Jared Hecht, A Crash Course in the Small-Business Bailout, April 10, 2020, at https://www.barrons.com/articles/a-crash-course-in-the-small-business-bailout-51586553690.

[49] Peapack-Gladstone Bank, Lessons Learned: What the SBA's PPP Loan Process Revealed to us About Small Businesses and Our Bank, at https://www.pgbank.com/assets/files/3vOujTxD.

[50] Congressional testimony: Samuel C. Scott III, Testimony Before the United States House of Representative Committee on Financial Services Subcommittee on Consumer Protection and Financial Institutions, June 3, 2020; Talibah M. Bayles, Testimony Before the United States Senate Committee on Small Business & Entrepreneurship, July 23, 2020. Policy proposal: Black Economic Alliance, The Black Economic Alliance Calls on Congress to Include Key Initiatives to Help Black Businesses, Workers, Universities, and Cultural Institutions in Next COVID-19 Legislation, at https://blackeconomicalliance.org/app/uploads/2020/04/Black-Economic-Alliance-PPP-Stimulus-Proposal1.pdf. Interviews with Black business owners: Josephin Peterson, Being a Black business owner is difficult in Pierce County. Here's the biggest reason, July 18, 2022, at https://www.thenewstribune.com/news/local/article250639364.html. See also: Ashley Portero, Opportunity Knocks: Community Banks Poised to Gain New Business After Crisis, June 12, 2020, at https://www.bizjournals.com/southflorida/news/2020/06/12/0612-cp-opportunity-knocks-for-local-banks.html; Samantha Masunaga and Taylor Avery, Black-Owned Businesses Face a System Set Up Against Them. COVID-19 Makes it Worse, June 20, 2020, at https://www.latimes.com/business/story/2020-06-20/black-owned-business-loans-banks.

Can" to simplify and expedite the PPP application process for minority-owned small businesses.[51] The CEO of Paybby, Hassan Miah, spoke about PPP application challenges for minority business owners:[52]

> When PPP came out, the first round, people of color were underrepresented. Either they didn't know [about the program] or they had issues getting their data...When we first got involved, Carver [a Black-owned bank] and some of [the] banks we talked with told us that in the Black community many people don't even have a bank account. We saw this as an opportunity to provide that account and then support them on their loan efforts. Many of these small businesses are small Mom and Pop businesses, many of them work out of their back pockets: they use their regular personal checking account, make no distinction between their social security number and EIN, and those kinds of things.

To provide more systematic evidence that Black-owned firms were more affected by the administrative burdens of the PPP approval process, we ask whether Black-owned firms receiving PPP loans are less likely to receive the full amount they requested. There are three reasons why a firm would receive a smaller amount of PPP funding than it requested: (i) choosing to accept less than the full approved amount; (ii) providing insufficient documentation; or (iii) requesting a loan in excess of the eligible amount.[53] While some firms did accept less than their approved amounts, the PPP administrative data indicates that this was quite rare: less than 3% of 2020 loans list a "current approval amount" smaller than the "initial approval amount."[54] Moreover, firms in our data that report receiving less than their full requests are substantially more likely to apply for other forms of credit, suggesting that they were not choosing to take less than their approved

[51] Other examples of programs designed to assist Black- and other minority-owned businesses with PPP applications include: Luminary Evaluation Group, Home Grown Technical Assistance Program for the Paycheck Protection Program, September 1, 2020, at https://homegrownchildcare.org/wp-content/uploads/2020/12/Home-Grown-PPP-Project-Outcomes-Report_Luminary_Septembr-2020.pdf; Our Fair Share, at https://www.ourfairshare.com/about/.

[52] David Penn, PPP, Diversity, and the Power of Fintech Paterships, March 4, 2021, at https://finovate.com/ppp-diversity-and-the-power-of-fintech-partnerships/.

[53] Some firms likely made mistakes that led them to request less than their maximum eligible amount, not more. However, the most common mistakes made on payroll calculations invariably led firms to over-estimate their loan amounts. Alternatively, some firms may have intentionally applied for less than the maximum amount for which they were eligible. This too was likely rare: the application form treated the requested loan amount as the maximum eligible loan amount, as did essentially all guidance and advice one can find online about submitting PPP applications.

[54] SBA, Procedural Notice 5000-200076, January 13, 2021, at

https://www.sba.gov/sites/default/files/2021-03/Procedural%20Notice%205000-20076%20First%20Draw%20PPP%20Loan%20Increases%201.13.21-508.pdf.

amounts.

We can therefore attribute "funding shortages" to issues related to the administrative burdens of the PPP, whether due to insufficient documentation or an excessive loan amount request. Regarding insufficient documentation, it is possible that although a firm correctly calculated the amount for which it was eligible, the firm did not supply sufficient documentation to substantiate portions of its request. For example, the firm may have had accurate but informal internal records of contributions to benefits programs that did not meet program standards of proof. Alternatively, a firm may simply have requested more funds than it was eligible for under program rules. Including payments to contract workers as payroll costs is an example of one such miscalculation.

Table 8 displays the results. About one fifth of all firms approved for PPP receive less than the amount requested. Younger and smaller firms are significantly less likely to receive the full amount requested, as are firms using contract workers. This is true of both bank and fintech loans, although the results for fintech loans are statistically weaker, probably because of the much smaller sample size. The lower likelihood that firms using contract workers receive the full request is consistent with the idea that funding shortfalls reflect loan requests in excess of the eligible amount. In untabulated results, we find that employer businesses are 7.3 percentage points less likely to receive the full amount requested at banks. This lower approval rate could also reflect loan requests in excess of the eligible amount, given that employer firms had to provide more documentation and also perform more complex loan amount calculations.

In column 1, we find that Black-owned firms that receive PPP loans from banks are 20.3 percentage points less likely than observably similar white-owned firms to receive the full amount requested. This finding does not appear to be due to lower relative approval rates of Black-owned firms in more racially biased counties: the coefficients on the interactions of *Black* with the explicit and implicit bias measures in columns 2 and 3 are small and not statistically significant. In column 4, we find an even larger disparity at fintechs. Conditional on being approved by a fintech, Black-owned firms are 25.4 percentage points less likely than white-owned firms to receive the full amount requested. Columns 5 and 6 again demonstrate that the lower funding level relative to the requested amount is not related to racial bias. Taken together, the findings in Table 8 suggest that Black-owned firms may have had more difficulty providing the required documentation or were more likely to request an amount in excess of the eligible amount. Along the lines of the survey evidence, this could be explained by the lower likelihood that Black-owned firms had professional support in the preparation of their applications.

6 Conclusion

We use the 2020 Small Business Credit Survey, which includes detailed information on PPP loan applications and approvals, along with information on owner race, gender, and Hispanic origin, to unpack the sources of racial disparities in the take-up of PPP loans and to study the effects of racial bias on both loan applications and approvals. We find that, controlling for firm characteristics, Black- and Hispanic-owned firms are 4.9 and 4.5 percentage points less likely than observably similar white-owned firms to apply for PPP loans. For Black-owned firms, this effect is driven by a lower probability of applying for PPP loans from banks. Conditional on applying for a PPP loan, Black-owned firms are 9.9 percentage points less likely to apply at banks and 7.8 percentage points more likely to apply at fintechs. The substitution away from bank applications and toward fintech applications is stronger in more racially biased counties, and could be driven by either historical discrimination that discourages Black-owned firms from approaching banks in the first place or by banks in more racially biased counties providing worse service to Black-owned firms.

Application behavior alone is enough to explain the previously-documented finding that Black-owned firms are more likely than white-owned firms to receive PPP loans from fintechs (Chernenko and Scharfstein, 2023; Howell et al., 2024). By contrast, approval rates at banks and fintechs cannot explain the greater reliance of Black-owned firms on fintechs, as we find similar approval disparities at banks and fintechs. Compared to observably similar white-owned firms, Black-owned firms are 7.4 percentage points less likely to be approved at banks and 8.4 percentage points less likely to be approved at fintechs.

Our analysis suggests three main reasons for approval disparities at both banks and fintechs. First, we show that observable differences between Black- and white-owned firms explain almost half of the unconditional gap in approval rates. In other words, Black-owned firms are more likely to have characteristics (e.g., younger, lower revenues, and fewer employees) associated with lower approval rates. Second, we show that racial bias is related to bank approval outcomes; in counties with more racial bias, Black-owned firms applying to banks are significantly less likely than observably similar white-owned firms to receive funding. This could be because racial bias directly affected approval decisions at banks, or because the legacy of racial bias means that Black-owned firms were less likely to have access to the financial resources that would have made approval more likely. A third reason for approval disparities — supported by both anecdotal and empirical evidence — is that a larger fraction of Black-owned businesses had difficulty with the administrative burdens of the PPP, and in particular with determining eligible loan amounts and providing the required documentation. In other words, the administrative burdens of the PPP application process disproportionately affected the approval rates of Black-owned firms. While we cannot pinpoint the exact reason why Black-owned firms were disproportionately affected by the administrative burdens of the program, survey evidence suggests that one reason may be that they were less likely to have relationships with professional service providers such as lawyers and accountants and thus were less likely to receive help from them in the application process. This is also the case for smaller and younger firms.

Importantly, both differences in observable characteristics and in the impact of administrative burdens may themselves be driven by the historical legacy of racial bias. The fact that Black-owned firms tend to have lower revenues and fewer employees than white-owned businesses may be related to past instances of racially discriminatory treatment — such as in prior applications and approvals for credit — that affected a firm's financial condition (Fairlie, Robb, and Robinson, 2021; Kim et al., 2021). Racial disparities in the impact of administrative burdens may similarly be related to widely-documented racial disparities in access to financial services.

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Table 1
Summary Statistics

This table reports sample means broken out by owners' racial and Hispanic identity, and by gender. Population and median household income are in thousands. Branches per capita is scaled by 1000 (i.e., number of branches per 1000 people) and is winsorized at the 99% level. The sample is composed of survey respondents who report (i) information for all outcome and control variables; (ii) majority white, Black, Asian, or Hispanic ownership. In this table, but *not* throughout the rest of the paper, a small number of respondents (1%–2% of the sample) reporting multiracial/ethnic majority ownership are excluded.

		Race/Ethnicity				Gender	
	Total	White	Black	Asian	Hispanic	Male	Female
$N =$	11,841	8,424	1,654	753	1,010	7,073	4,768
Firm Characteristics							
# Owners + Employees	9.12	10.33	4.54	7.73	7.57	11.02	6.31
# Years in Business	16.57	18.83	9.93	12.27	11.83	18.43	13.82
2019 Revenues \$0-\$25k	0.12	0.09	0.30	0.08	0.13	0.09	0.17
2019 Revenues \$25k-\$50k	0.09	0.07	0.15	0.07	0.11	0.06	0.12
2019 Revenues \$50k-\$100k	0.12	0.10	0.17	0.11	0.14	0.10	0.14
2019 Revenues $\geq$ \$100k	0.68	0.74	0.37	0.74	0.62	0.74	0.58
2019 Loss	0.20	0.18	0.34	0.20	0.19	0.19	0.22
2019 Break-Even	0.17	0.16	0.22	0.17	0.20	0.17	0.18
2019 Profit	0.62	0.66	0.44	0.63	0.61	0.64	0.60
Owner Age $<$ 45	0.20	0.17	0.30	0.26	0.26	0.18	0.24
Owner Age 45-64	0.60	0.60	0.57	0.62	0.61	0.59	0.61
Owner Age $\geq$ 65	0.20	0.23	0.13	0.12	0.13	0.23	0.15
Employer Business	0.71	0.72	0.63	0.76	0.72	0.74	0.65
Uses Contract Workers	0.46	0.44	0.54	0.41	0.51	0.44	0.48
ZIP Code Characteristics							
Branches Per Capita	0.36	0.38	0.29	0.36	0.32	0.37	0.35
Population (000s)	29.51	27.52	33.70	32.72	36.79	29.19	29.98
Median Household Income (\$000s)	71.70	72.37	63.86	85.78	68.36	71.57	71.89
Fraction White	0.59	0.66	0.41	0.47	0.42	0.60	0.58
Unemployment Rate	0.03	0.03	0.04	0.03	0.03	0.03	0.03
Outcomes							
Applied for PPP	0.67	0.71	0.49	0.75	0.62	0.70	0.63
Bank	0.57	0.61	0.34	0.65	0.49	0.61	0.51
Fintech	0.09	0.08	0.14	0.11	0.11	0.09	0.11
CU/CDFI	0.05	0.05	0.07	0.03	0.06	0.05	0.06
Received PPP	0.63	0.67	0.40	0.73	0.56	0.66	0.58
Bank	0.52	0.57	0.28	0.61	0.44	0.56	0.46
Fintech	0.07	0.06	0.08	0.09	0.07	0.06	0.08
CU/CDFI	0.04	0.04	0.04	0.03	0.04	0.04	0.04

Table 2
Black-Owned Firms and PPP Access

Columns 1–2 report the results of linear probability model regressions of receiving a PPP loan. Columns 3–6 report the results of linear probability model regressions of receiving a PPP loan from a bank, conditional on receiving a PPP loan from any lender. Columns 1–4 report robust standard errors. In columns 5–6, standard errors are clustered by county. Racial bias measures are standardized to have zero mean and unit variance. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Received PPP		Received Bank PPP | Received PPP			
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.257***	−0.089***	−0.142***	−0.092***	−0.092***	−0.093***
	(0.013)	(0.012)	(0.018)	(0.018)	(0.019)	(0.019)
Black × Explicit Bias					−0.114***	
					(0.040)	
Black × Implicit Bias						−0.127***
						(0.048)
Asian	0.055***	0.016	0.003	0.015	0.014	0.015
	(0.016)	(0.015)	(0.015)	(0.017)	(0.018)	(0.018)
Hispanic	−0.084***	−0.061***	−0.033*	0.001	0.005	0.002
	(0.016)	(0.014)	(0.018)	(0.018)	(0.020)	(0.020)
Female	−0.054***	0.029***	−0.051***	−0.019**	−0.019**	−0.019**
	(0.009)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
Firm Characteristics						
Log(Owners + Employees)		0.074***		0.035***	0.035***	0.035***
		(0.004)		(0.004)	(0.005)	(0.005)
Log(Years in Business)		0.007*		0.021***	0.021***	0.021***
		(0.004)		(0.005)	(0.006)	(0.005)
$25k-$50k		0.076***		−0.024	−0.025	−0.025
		(0.017)		(0.045)	(0.041)	(0.041)
$50k-$100k		0.135***		0.052	0.050	0.049
		(0.017)		(0.040)	(0.042)	(0.042)
More than $100k		0.396***		0.123***	0.121***	0.119***
		(0.015)		(0.036)	(0.035)	(0.036)
Break-Even		−0.024*		0.009	0.009	0.009
		(0.015)		(0.016)	(0.017)	(0.017)
Profit		0.012		0.005	0.005	0.005
		(0.012)		(0.013)	(0.013)	(0.013)
Owner Age 45-64		−0.029***		0.030**	0.029**	0.028**
		(0.010)		(0.012)	(0.012)	(0.012)
Owner Age ≥ 65		−0.081***		0.049***	0.048***	0.048***
		(0.012)		(0.015)	(0.014)	(0.014)
Employer Business		0.242***		−0.018	−0.018	−0.015
		(0.018)		(0.046)	(0.044)	(0.044)
Nonemployer × Break-Even		0.026		−0.042	−0.044	−0.042
		(0.023)		(0.062)	(0.059)	(0.059)
Nonemployer × Profit		0.093***		−0.035	−0.033	−0.032
		(0.020)		(0.048)	(0.045)	(0.045)
Uses Contract Workers		−0.023***		−0.011	−0.011	−0.010
		(0.007)		(0.009)	(0.008)	(0.008)
N	12,229	12,229	7,607	7,607	7,607	7,607
R^2	0.05	0.38	0.02	0.09	0.09	0.09
Mean of Dependent Variable	0.62	0.62	0.83	0.83	0.83	0.83
State FEs		✓		✓		✓
Industry FEs		✓		✓		✓
ZIP controls		✓		✓		✓

Table 3
Which Firms Apply for PPP?

This table reports the results of linear probability model regressions of applying for a PPP loan. In order to match the sample used in Table 2, firms that report applying for PPP but do not report whether they received PPP funds are excluded from all regressions in the table. The dependent variable is equal to one if the firm applied for a PPP loan from any lender. Columns 1, 2, and 5 report robust standard errors. In columns 3–4, standard errors are clustered by county. Racial bias measures are standardized to have zero mean and unit variance. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)
Black	−0.194***	−0.049***	−0.048***	−0.049***	−0.038***
	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
Black × Explicit Bias			−0.010		
			(0.030)		
Black × Implicit Bias				0.014	
				(0.037)	
Asian	0.049***	0.003	0.003	0.003	0.008
	(0.016)	(0.014)	(0.019)	(0.019)	(0.014)
Hispanic	−0.057***	−0.045***	−0.045***	−0.045***	−0.039***
	(0.016)	(0.014)	(0.015)	(0.015)	(0.014)
Female	−0.052***	0.022***	0.023***	0.022***	0.022***
	(0.009)	(0.007)	(0.008)	(0.008)	(0.007)
Firm Characteristics					
Current Bank Relationship					0.113***
					(0.010)
Log(Owners + Employees)		0.062***	0.062***	0.062***	0.059***
		(0.004)	(0.004)	(0.004)	(0.004)
Log(Years in Business)		−0.000	0.000	0.000	−0.002
		(0.004)	(0.004)	(0.004)	(0.004)
$25k-$50k		0.116***	0.116***	0.117***	0.110***
		(0.018)	(0.017)	(0.017)	(0.018)
$50k-$100k		0.151***	0.150***	0.150***	0.140***
		(0.018)	(0.018)	(0.018)	(0.018)
More than $100k		0.389***	0.388***	0.388***	0.371***
		(0.016)	(0.016)	(0.016)	(0.016)
Break-Even		−0.025*	−0.025*	−0.025*	−0.025*
		(0.014)	(0.014)	(0.014)	(0.014)
Profit		0.001	0.001	0.001	0.001
		(0.011)	(0.011)	(0.011)	(0.011)
Owner Age 45-64		−0.034***	−0.034***	−0.033***	−0.032***
		(0.010)	(0.010)	(0.010)	(0.010)
Owner Age $\geq$ 65		−0.087***	−0.087***	−0.087***	−0.083***
		(0.012)	(0.012)	(0.012)	(0.012)
Employer Business		0.244***	0.244***	0.244***	0.242***
		(0.019)	(0.018)	(0.018)	(0.019)
Nonemployer × Break-Even		0.012	0.012	0.012	0.017
		(0.025)	(0.024)	(0.024)	(0.025)
Nonemployer × Profit		0.089***	0.088***	0.088***	0.094***
		(0.021)	(0.020)	(0.020)	(0.021)
Uses Contract Workers		−0.008	−0.008	−0.008	−0.011
		(0.007)	(0.007)	(0.007)	(0.007)
N	12,229	12,229	12,207	12,207	12,164
R^2	0.03	0.34	0.34	0.34	0.35
Mean of Dependent Variable	0.67	0.67	0.67	0.67	0.67
State FEs		✓	✓	✓	✓
Industry FEs		✓	✓	✓	✓
ZIP controls		✓	✓	✓	✓

Table 4
Why Do Some Firms Not Apply for PPP?

This table reports the results of linear probability model regressions of possible reasons that non-applicants cite for not applying for a PPP loan:

$$Reason_f = \alpha + \beta \cdot Minority_f + \gamma' X_f + \varepsilon_f,$$

where f indexes firms. The sample consists of firms that did not apply for a PPP loan. Robust standard errors are reported. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%. $N = 3,923$.

	Unneeded (1)	No Gov. (2)	Eligibility (3)	No Lenders (4)	Confusing (5)	Unaware (6)	Deadline (7)
Black	−0.074***	−0.021**	−0.008	0.019	0.058***	0.047***	0.074***
	(0.014)	(0.009)	(0.023)	(0.015)	(0.019)	(0.015)	(0.014)
Asian	−0.048**	−0.045***	0.040	0.031	0.001	0.081***	0.049**
	(0.022)	(0.010)	(0.037)	(0.026)	(0.030)	(0.026)	(0.025)
Hispanic	−0.061***	−0.014	−0.027	0.002	0.043*	0.067***	0.071***
	(0.018)	(0.012)	(0.030)	(0.020)	(0.025)	(0.020)	(0.020)
Female	−0.014	−0.006	0.016	−0.011	0.008	−0.018*	−0.014
	(0.012)	(0.008)	(0.017)	(0.011)	(0.014)	(0.010)	(0.010)
Firm Characteristics							
Log(Owners + Employees)	0.019*	0.024***	−0.007	−0.009	−0.008	−0.013*	−0.006
	(0.010)	(0.009)	(0.013)	(0.007)	(0.010)	(0.007)	(0.007)
Log(Years in Business)	0.010*	−0.002	−0.013	−0.004	0.008	−0.006	−0.001
	(0.006)	(0.004)	(0.009)	(0.006)	(0.007)	(0.005)	(0.005)
$25k-$50k	−0.075***	−0.004	0.019	0.025	0.033	−0.001	0.018
	(0.016)	(0.011)	(0.026)	(0.015)	(0.021)	(0.017)	(0.015)
$50k-$100k	−0.057***	−0.015	0.010	0.050***	0.041**	−0.010	0.014
	(0.017)	(0.011)	(0.026)	(0.016)	(0.021)	(0.016)	(0.015)
More than $100k	−0.037**	0.006	−0.001	0.019	−0.002	−0.052***	0.011
	(0.018)	(0.011)	(0.026)	(0.016)	(0.021)	(0.015)	(0.015)
Break-Even	0.008	0.020	−0.040	−0.012	−0.013	−0.006	−0.021
	(0.018)	(0.016)	(0.037)	(0.028)	(0.033)	(0.024)	(0.025)
Profit	0.096***	0.017	−0.130***	−0.044*	−0.042	−0.019	−0.029
	(0.018)	(0.013)	(0.031)	(0.023)	(0.028)	(0.020)	(0.021)
Owner Age 45-64	0.015	−0.008	−0.011	−0.018	0.005	−0.000	−0.017
	(0.012)	(0.009)	(0.021)	(0.014)	(0.017)	(0.013)	(0.013)
Owner Age $\geq$ 65	0.072***	0.007	−0.044*	−0.032*	−0.012	−0.013	−0.017
	(0.019)	(0.012)	(0.027)	(0.017)	(0.022)	(0.015)	(0.016)
Employer Business	−0.044**	−0.025*	−0.134***	0.089***	0.075***	0.029	0.061***
	(0.019)	(0.014)	(0.034)	(0.024)	(0.029)	(0.022)	(0.021)
Nonemployer × Break-Even	0.005	−0.032	−0.015	0.025	0.025	0.008	0.030
	(0.026)	(0.020)	(0.047)	(0.032)	(0.040)	(0.030)	(0.029)
Nonemployer × Profit	−0.013	−0.003	0.007	0.037	0.039	0.007	0.020
	(0.024)	(0.016)	(0.039)	(0.027)	(0.033)	(0.024)	(0.024)
Uses Contract Workers	−0.052***	0.006	0.036**	0.014	0.055***	−0.025***	−0.007
	(0.011)	(0.008)	(0.017)	(0.010)	(0.014)	(0.010)	(0.010)
R^2	0.11	0.04	0.06	0.05	0.03	0.05	0.04
Mean of Dependent Variable	0.14	0.06	0.45	0.11	0.20	0.10	0.09
State FEs	✓	✓	✓	✓	✓	✓	✓
Industry FEs	✓	✓	✓	✓	✓	✓	✓
ZIP Controls	✓	✓	✓	✓	✓	✓	✓

Table 5
Where do Firms Apply for PPP?

This table reports the results of linear probability model regressions of applying for a PPP loan with a given lender type, within the sample of firms applying for PPP. As in Table 3, firms that report applying for PPP but do not report whether they received PPP funds are excluded from all regressions in the table. In columns 1–5 (6–10), the dependent variable is equal to one if the firm applied for a PPP loan from a bank (fintech). In columns 3–4 and 8–9, standard errors are clustered by county. In all other columns, robust standard errors are reported. Racial bias measures are standardized to have zero mean and unit variance. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Applied to Bank					Applied to Fintech				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Black	−0.165***	−0.099***	−0.098***	−0.099***	−0.085***	0.147***	0.078***	0.077***	0.077***	0.075***
	(0.016)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)
Black × Explicit Bias			−0.095**					0.071*		
			(0.039)					(0.040)		
Black × Implicit Bias				−0.109**					0.099**	
				(0.048)					(0.047)	
Asian	0.006	0.013	0.012	0.013	0.029*	0.015	−0.001	0.001	−0.001	−0.006
	(0.014)	(0.015)	(0.017)	(0.017)	(0.015)	(0.015)	(0.016)	(0.017)	(0.017)	(0.016)
Hispanic	−0.045***	−0.012	−0.009	−0.011	−0.001	0.044***	0.007	0.004	0.006	0.001
	(0.017)	(0.017)	(0.018)	(0.018)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Female	−0.047***	−0.014*	−0.015*	−0.014*	−0.014*	0.039***	0.011	0.011	0.011	0.011
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Firm Characteristics										
Current Bank Relationship					0.273***					−0.085***
					(0.015)					(0.013)
Log(Owners + Employees)		0.035***	0.035***	0.035***	0.026***		−0.028***	−0.028***	−0.028***	−0.025***
		(0.004)	(0.004)	(0.004)	(0.004)		(0.004)	(0.004)	(0.004)	(0.004)
Log(Years in Business)		0.019***	0.019***	0.019***	0.015***		−0.013***	−0.013***	−0.013***	−0.012**
		(0.005)	(0.005)	(0.005)	(0.005)		(0.005)	(0.004)	(0.004)	(0.005)
$25k-$50k		0.007	0.005	0.005	0.017		0.015	0.016	0.017	0.008
		(0.038)	(0.037)	(0.037)	(0.036)		(0.037)	(0.036)	(0.036)	(0.037)
$50k-$100k		0.107***	0.103***	0.102***	0.089***		−0.092***	−0.090***	−0.088**	−0.088***
		(0.033)	(0.035)	(0.035)	(0.032)		(0.033)	(0.034)	(0.034)	(0.033)
More than $100k		0.174***	0.171***	0.170***	0.154***		−0.150***	−0.149***	−0.147***	−0.146***
		(0.030)	(0.030)	(0.030)	(0.029)		(0.030)	(0.030)	(0.030)	(0.030)
Break-Even		0.007	0.007	0.007	0.006		−0.015	−0.015	−0.015	−0.014
		(0.015)	(0.016)	(0.016)	(0.015)		(0.015)	(0.016)	(0.016)	(0.015)
Profit		0.006	0.006	0.006	0.006		−0.022*	−0.022*	−0.022*	−0.022*
		(0.012)	(0.012)	(0.012)	(0.012)		(0.012)	(0.012)	(0.012)	(0.012)
Owner Age 45-64		0.021*	0.021*	0.021*	0.020*		−0.017	−0.017	−0.017	−0.017
		(0.011)	(0.011)	(0.011)	(0.011)		(0.011)	(0.012)	(0.012)	(0.011)
Owner Age $\geq$ 65		0.034**	0.033***	0.033***	0.033**		−0.042***	−0.042***	−0.042***	−0.042***
		(0.014)	(0.013)	(0.013)	(0.013)		(0.013)	(0.014)	(0.014)	(0.013)
Employer Business		−0.025	−0.025	−0.023	−0.018		0.031	0.031	0.030	0.030
		(0.036)	(0.035)	(0.036)	(0.035)		(0.037)	(0.038)	(0.038)	(0.036)
Nonemployer × Break-Even		−0.041	−0.041	−0.041	−0.016		0.046	0.046	0.046	0.036
		(0.049)	(0.048)	(0.048)	(0.047)		(0.050)	(0.046)	(0.046)	(0.049)
Nonemployer × Profit		−0.052	−0.051	−0.051	−0.041		0.044	0.042	0.042	0.041
		(0.038)	(0.037)	(0.037)	(0.037)		(0.039)	(0.037)	(0.037)	(0.038)
Uses Contract Workers		0.001	0.001	0.001	−0.000		0.018**	0.018**	0.018**	0.018**
		(0.008)	(0.008)	(0.008)	(0.008)		(0.008)	(0.007)	(0.007)	(0.008)
N	8,187	8,187	8,170	8,170	8,154	8,187	8,187	8,170	8,170	8,154
R^2	0.03	0.11	0.11	0.11	0.17	0.02	0.09	0.09	0.09	0.09
Mean of Dependent Variable	0.84	0.84	0.84	0.84	0.84	0.14	0.14	0.14	0.14	0.14
State FEs		✓	✓	✓	✓		✓	✓	✓	✓
Industry FEs		✓	✓	✓	✓		✓	✓	✓	✓
ZIP controls		✓	✓	✓	✓		✓	✓	✓	✓

Table 6
Which Firms Are Approved for PPP?

This table reports the results of linear probability model regressions of receiving a PPP loan, conditional on applying. In columns 1–2 (3–4), the sample consists of firms that applied for a PPP loan from a bank (fintech). In columns 5–6, the dependent variable is equal to one if the firm received a PPP loan from any lender. Robust standard errors are reported. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Bank		Fintech		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.116***	−0.074***	−0.154***	−0.084**	−0.144***	−0.081***
	(0.016)	(0.016)	(0.036)	(0.041)	(0.014)	(0.013)
Asian	0.013	0.020*	0.050	0.053	0.011	0.017*
	(0.010)	(0.012)	(0.047)	(0.050)	(0.009)	(0.009)
Hispanic	−0.033**	−0.021	−0.067	−0.053	−0.041***	−0.028**
	(0.014)	(0.015)	(0.048)	(0.051)	(0.012)	(0.012)
Female	−0.014**	0.004	0.030	0.037	−0.008	0.013**
	(0.007)	(0.007)	(0.027)	(0.028)	(0.006)	(0.006)
Firm Characteristics						
Relationship w/Lender		−0.011		0.009		0.018**
		(0.010)		(0.029)		(0.008)
Log(Owners + Employees)		0.016***		−0.015		0.017***
		(0.003)		(0.019)		(0.002)
Log(Years in Business)		0.010**		0.016		0.007**
		(0.004)		(0.017)		(0.003)
$25k-$50k		0.009		0.007		0.031
		(0.045)		(0.066)		(0.035)
$50k-$100k		0.057		0.101		0.115***
		(0.038)		(0.065)		(0.031)
More than $100k		0.138***		0.179***		0.191***
		(0.035)		(0.060)		(0.028)
Break-Even		−0.005		0.045		−0.009
		(0.012)		(0.053)		(0.010)
Profit		0.002		0.067		0.001
		(0.009)		(0.042)		(0.008)
Owner Age 45-64		0.009		−0.049		−0.005
		(0.010)		(0.033)		(0.008)
Owner Age $\geq$ 65		0.008		−0.082		−0.016*
		(0.011)		(0.055)		(0.010)
Employer Business		0.232***		0.147*		0.221***
		(0.046)		(0.082)		(0.038)
Nonemployer × Break-Even		0.117*		0.054		0.117**
		(0.061)		(0.114)		(0.050)
Nonemployer × Profit		0.222***		0.166*		0.208***
		(0.047)		(0.088)		(0.039)
Uses Contract Workers		−0.026***		−0.006		−0.017***
		(0.007)		(0.028)		(0.005)
N	6,840	6,840	1,150	1,150	8,125	8,125
R^2	0.02	0.11	0.02	0.12	0.04	0.15
Mean of Dependent Variable	0.92	0.92	0.70	0.70	0.93	0.93
State FEs		✓		✓		✓
Industry FEs		✓		✓		✓
ZIP controls		✓		✓		✓

Table 7
Racial Bias and Approval Decisions

This table reports the results of linear probability model regressions of receiving a PPP loan, conditional on applying. In columns 1–2 (3–4), the sample consists of firms that applied for a PPP loan from a bank (fintech). In columns 5–6, the dependent variable is equal to one if the firm received a PPP loan from any lender. Standard errors are clustered by county. Racial bias measures are standardized to have zero mean and unit variance. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Bank		Fintech		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.074***	−0.075***	−0.081**	−0.084**	−0.080***	−0.080***
	(0.015)	(0.015)	(0.040)	(0.039)	(0.013)	(0.013)
Black × Explicit Bias	−0.076*		0.096		−0.045	
	(0.039)		(0.098)		(0.037)	
Black × Implicit Bias		−0.092**		0.075		−0.055
		(0.041)		(0.127)		(0.041)
N	6,824	6,824	1,150	1,150	8,108	8,108
R^2	0.11	0.11	0.12	0.12	0.16	0.16
Mean of Dependent Variable	0.92	0.92	0.70	0.70	0.93	0.93
State FEs	✓	✓	✓	✓	✓	✓
Industry FEs	✓	✓	✓	✓	✓	✓
Firm/ZIP Controls	✓	✓	✓	✓	✓	✓

Table 8
PPP Amount Requested vs Received

This table reports the results of linear probability model regressions of receiving the full amount of PPP funding requested, conditional on receiving a PPP loan from a given lender type:

$$FullAmount_{f,c} = \alpha + \beta_0 \cdot Minority_f + \beta_1 \cdot Black_f \times Bias_c + \gamma' X_f + \varepsilon_{f,c},$$

where f indexes firms and c indexes counties. Columns 1 and 4 report robust standard errors. In columns 2–3 and 5–6, standard errors are clustered by county. Racial bias measures are standardized to have zero mean and unit variance. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Bank			Fintech		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.203***	−0.203***	−0.203***	−0.253***	−0.264***	−0.256***
	(0.025)	(0.023)	(0.023)	(0.055)	(0.055)	(0.055)
Black × Explicit Bias		0.010			0.037	
		(0.071)			(0.137)	
Black × Implicit Bias			−0.000			0.016
			(0.083)			(0.187)
Asian	−0.068***	−0.066***	−0.066***	−0.094	−0.101*	−0.096*
	(0.022)	(0.023)	(0.023)	(0.067)	(0.057)	(0.057)
Hispanic	−0.052**	−0.052*	−0.052*	−0.037	−0.030	−0.037
	(0.023)	(0.029)	(0.029)	(0.062)	(0.061)	(0.061)
Female	−0.004	−0.004	−0.004	0.011	0.008	0.011
	(0.011)	(0.012)	(0.012)	(0.035)	(0.038)	(0.038)
Firm Characteristics						
Relationship w/Lender	−0.003	−0.003	−0.003	−0.075**	−0.072**	−0.074**
	(0.017)	(0.015)	(0.015)	(0.037)	(0.035)	(0.035)
Log(Owners + Employees)	0.023***	0.023***	0.023***	0.015	0.013	0.014
	(0.005)	(0.005)	(0.005)	(0.023)	(0.022)	(0.022)
Log(Years in Business)	0.026***	0.026***	0.026***	0.037*	0.036*	0.037*
	(0.006)	(0.006)	(0.006)	(0.021)	(0.021)	(0.021)
\$25k-\$50k	−0.057	−0.058	−0.058	−0.078	−0.091	−0.082
	(0.056)	(0.053)	(0.053)	(0.093)	(0.089)	(0.089)
\$50k-\$100k	−0.039	−0.039	−0.039	−0.117	−0.118	−0.118
	(0.048)	(0.048)	(0.048)	(0.093)	(0.080)	(0.081)
More than \$100k	0.069	0.069*	0.069*	−0.004	−0.009	−0.005
	(0.043)	(0.041)	(0.041)	(0.084)	(0.071)	(0.073)
Break-Even	−0.017	−0.017	−0.017	−0.007	−0.010	−0.009
	(0.020)	(0.021)	(0.021)	(0.066)	(0.068)	(0.068)
Profit	0.002	0.003	0.003	0.054	0.053	0.053
	(0.016)	(0.016)	(0.016)	(0.053)	(0.056)	(0.056)
Owner Age 45-64	−0.012	−0.012	−0.012	−0.014	−0.014	−0.014
	(0.015)	(0.014)	(0.014)	(0.044)	(0.048)	(0.048)
Owner Age $\geq$ 65	0.001	0.002	0.002	0.096	0.096	0.094
	(0.018)	(0.016)	(0.016)	(0.062)	(0.062)	(0.063)
Employer Business	−0.027	−0.028	−0.028	−0.052	−0.046	−0.052
	(0.059)	(0.056)	(0.056)	(0.125)	(0.122)	(0.125)
Nonemployer × Break-Even	−0.031	−0.030	−0.033	0.010	0.022	0.009
	(0.078)	(0.074)	(0.074)	(0.168)	(0.160)	(0.161)
Nonemployer × Profit	0.066	0.067	0.066	−0.052	−0.051	−0.052
	(0.061)	(0.057)	(0.057)	(0.131)	(0.121)	(0.123)
Uses Contract Workers	−0.062***	−0.062***	−0.062***	−0.035	−0.038	−0.036
	(0.010)	(0.010)	(0.010)	(0.036)	(0.034)	(0.034)
N	6,311	6,295	6,295	797	797	797
R^2	0.09	0.09	0.09	0.16	0.16	0.16
Mean of Dependent Variable	0.79	0.79	0.79	0.62	0.62	0.62
State FEs	✓	✓	✓	✓	✓	✓
Industry FEs	✓	✓	✓	✓	✓	✓
ZIP Controls	✓	✓	✓	✓	✓	✓

Appendix

Description of Documentation Requirements and Eligible Loan Amount Determination

To get a sense of the administrative burden inherent in successfully navigating the PPP application process, we note that a sole proprietor or single-member limited liability corporation (LLC) with paid employees in 2019 was required to submit the following documents along with their PPP application form:[55]

(i) 2019 IRS Form 1040, Schedule C (net income/loss from business).
(ii) Payroll processor reports from a recognized vendor (e.g., Intuit, ADP, Gusto) or both of the following: (a) 2019 IRS Form 941 from all four quarters (quarterly tax return);[56] (b) 2019 state unemployment tax returns from all four quarters.
(iii) Proof of employer contributions to any benefits programs (e.g., monthly invoices from benefit administrators for each program).
(iv) Payroll statement or similar documentation (e.g., IRS Form 941 for the first quarter of 2020) from the period covering February 15, 2020 to prove that the business was in operation and had paid employees.

Application checklists available online from various lenders indicate that additional documents were sometimes requested, including:

(i) Completed loan amount worksheet showing details of the calculations underlying the requested loan amount.
(ii) 2019 IRS Forms W-2 and W-3 (wage and salary compensation) for all paid employees (if a payroll processor report providing such information was not included with the application).
(iii) 2019 Profit-and-Loss statement or balance sheet.

Finally, lenders often required more information from applicants with whom they did not have existing relationships for the purposes of satisfying Bank Secrecy Act (BSA) and Anti-Money Laundering (AML) guidelines, such as:

(i) Proof of business activation and "good standing" from the office of the secretary of state.
(ii) Certificate of fictitious name ("doing business as" name) or of sole proprietorship.
(iii) Completion of a beneficial ownership certification form, customer identification program form, and/or business identification form.
(iv) Voided business check.

In addition to providing documentation, sole proprietors and single-member LLCs were instructed

[55] SBA, Paycheck Protection Program How To Calculate Maximum Loan Amounts – By Business Type, April 24, 2020, at https://www.sba.gov/sites/default/files/2020-04/How-to-Calculate-Loan-Amounts.pdf.

[56] Applicants were able to submit their 2019 IRS Form 940 (annual federal unemployment tax return) in place of Form 941.

to make the following calculations to determine eligible payroll costs.[57]

(i) Net profit, from line 31 on IRS Form 1040 Schedule C. If greater than $100,000, this should be reduced to $100,000. If less than zero, it should be set to 0.
(ii) 2019 gross wages and tips paid to employees, from 2019 IRS Form 941 line 5c-column 1, plus pre-tax employee contributions for health insurance or other fringe benefits excluded from Taxable Medicare wages and tips. Add this figure across all four 941's submitted for 2019. For any employee paid in excess of $100,000 over the course of 2019, reduce their contribution to this final figure to $100,000.
(iii) 2019 employer contributions for employee health insurance, from the portion of IRS Form 1040 Schedule C line 14 attributable to health insurance.
(iv) 2019 employer contributions to employee retirement plans, from IRS Form 1040 Schedule C line 19.
(v) 2019 employer state and local taxes assessed on employee compensation (primarily state unemployment insurance taxes, from state quarterly wage reporting forms).

Other business structures, such as multi-member limited liability corporations, partnerships, and C- and S-corporations, were required to provide analogous (and usually more complex) tax forms and payroll records. For AML purposes, these firms were sometimes required to supply additional documentation, such as articles of organization or incorporation and company by-laws.

While the loan amount calculations were straightforward, they could require combining information from a large number of documents: an annual federal tax return; four quarterly federal tax returns; four quarterly state tax returns; and monthly or quarterly statements or invoices from health insurers and from retirement program administrators. Furthermore, there was substantial confusion about what to include in the calculations: whether employer-side federal payroll taxes constituted payroll costs (they did not); whether payments to contract workers constituted gross wages and tips (they did not); and the definition of "fringe benefits" (which was not provided in SBA guidance until January of 2021).

[57] Many payroll processors offered "PPP reports," which would automatically calculate eligible loan amounts of a firm's behalf. Even for firms using payroll processors that did not offer this service, payroll records provided streamlined and centralized access to all necessary inputs for loan amount calculations. Firms that did not use payroll processors faced greater difficulty calculating payroll costs.

Model of Endogenous Selection

There are two types of lenders that make PPP loans: banks and fintechs. Banks are different from fintechs in two ways. First, because banks generally use less automated processes and because they may engage in greater due diligence (including more robust Bank Secrecy Act and Anti-Money Laundering compliance), it is more costly for firms to apply for PPP loans from banks than from fintechs. Let the cost of applying for a loan from a bank be c_b, which is greater than the cost of applying to a loan from a fintech, c_f.

Second, because the bank loan application process often involves individual loan officers, there is scope for racial bias to enter into PPP loan application decisions. To model discrimination, let θ be the probability that a white-owned firm is approved for a PPP loan regardless of whether the firm applies to a bank or fintech. The probability θ measures the "condition" of the loan application, including whether the applicant is eligible for the loan, how complete the documentation is, and whether the loan amount calculations are done correctly. We assume the applicant knows this probability and that it is distributed uniformly on $[\theta_L, \theta_H]$. Black-owned firms face possible discrimination at banks, thereby lowering the probability of loan approval at banks to $\eta\theta$, where $\eta < 1$. Thus, for a given θ, Black-owned firms are less likely than white-owned firms to get their loans approved at banks. At fintechs, Black-owned firms face no discrimination, so the loan approval probability is θ. The distribution of θ for Black-owned firms is also uniformly distributed but shifted down by ϕ, which reflects unobserved attributes of Black-owned firms that make their applications more difficult to process. While the parameter ϕ is not the result of direct discrimination, it could reflect historical discrimination that made it more difficult for Black-owned firms to get the professional support necessary to enable more complete documentation and correct loan amount calculations.

Finally, suppose that the benefit of receiving a loan from a fintech is normalized to 1 whereas the benefit of receiving a loan from a bank is $R > 1$. This reflects, among other things, the idea that banks have more products from which a firm could benefit in the future.

Application and Approval Rates for White-Owned Firms

In this formulation, white-owned firms will apply to banks provided

$$\theta R - c_b \geq \theta - c_f$$

or

$$\theta \geq \frac{\Delta}{R-1}$$

where Δ is the application cost differential, $c_b - c_f$. A fraction $[\theta_H - \frac{\Delta}{R-1}]/[\theta_H - \theta_L]$ of white-owned firms apply to banks. The remaining share of white-owned firms either apply to fintechs or, if their approval probability is sufficiently low, they do not apply for a PPP loan. The fraction applying to fintechs is

$$\frac{\frac{\Delta}{R-1} - \max(\theta_L, c_f)}{\theta_H - \theta_L}$$

where all firms apply for a loan provided $\theta_L \geq c_f$ and $[c_f - \theta_L]/[\theta_H - \theta_L]$ do not apply for a loan if $\theta_L < c_f$.

We can now write the approval rate of white-owned firm applicants to banks, $A(w, b)$, as:

$$A(w, b) = \frac{1}{2}\left[\theta_H + \frac{\Delta}{R-1}\right] \tag{1}$$

The fintech approval rate for white-owned firms, $A(w, f)$, is:

$$A(w, f) = \frac{1}{2}\left[\max(\theta_L, c_f) + \frac{\Delta}{R-1}\right] \tag{2}$$

Application and Approval Rates for Black-Owned Firms

The conditions that determine whether Black-owned firms apply to banks or fintechs are different because of the potential for discrimination at banks. In particular, the condition for a Black-owned firm to apply to a bank is:

$$\eta\theta R - c_b \geq \theta - c_f$$

or

$$\theta \geq \frac{\Delta}{\eta R - 1}$$

Black-owned firms with the same θ as a white-owned firm are less likely to apply to a bank because of the discrimination factor η. An increase in discrimination – i.e., lower η – results in an increase in the average approval probability of Black-owned firms applying to banks. The fraction applying to banks is:

$$\frac{\theta_H - \phi - \Delta/(\eta R - 1)}{\theta_H - \theta_L}$$

The fraction applying to fintechs is:

$$\frac{\Delta/(\eta R - 1) - \max(\theta_L - \phi, c_f)]}{(\theta_H - \theta_L)}$$

For any $\phi > 0$, one can show that conditional on applying and relative to white-owned applicants: (i) a strictly lower fraction of Black-owned firms apply to banks; and (ii) a strictly higher fraction of Black-owned firms apply to fintechs. This is the case regardless of the level of bank bias, and even if there is no bank bias (i.e., $\eta = 1$). The approval rate for Black-owned bank PPP loan applicants, $A(B, b)$, is:

$$A(B, b) = \frac{\eta}{2}\left[\theta_H - \phi + \frac{\Delta}{\eta R - 1}\right] \tag{3}$$

An increase in bias has two countervailing effects on the bank approval rate of Black-owned firms. The direct effect is to lower the approval rate for all Black-owned firm applicants. The indirect effect is that some lower-θ Black-owned firms decide to apply to fintechs instead of banks, which increases the average level of θ among Black-owned firms applying to banks and thus increases the approval rate. Whether an increase in bias increases or decreases the bank approval rate depends on the parameters. For example, if ϕ is relatively low – the average θ of Black-owned firm applications is similar to that of white-owned firms – then an increase in bias will tend to lower the approval rate.

At fintechs, the approval rate for Black-owned firms, $A(B, f)$, is:

$$A(B, f) = \frac{1}{2}\left[\max(\theta_L - \phi, c_f) + \frac{\Delta}{\eta R - 1}\right] \tag{4}$$

An increase in bank bias unambiguously increases the fintech approval rate of Black-owned firms through the same indirect selection effect just discussed in the context of banks: the Black-owned firms that substitute from bank to fintech applications in response to increased bank bias have higher values of θ than other Black-owned firms applying to fintechs. An increase in bias also unambiguously increases the fraction of Black-owned firms that apply for loans at fintechs.

Approval Disparities at Banks and Fintechs

Given the above approval rates we can calculate the approval disparities at banks and fintechs. At fintechs, the approval disparity, $A(w, f) - A(B, f)$, is given by:

$$A(w, f) - A(B, f) = \frac{1}{2}\left[\max(\theta_L, c_f) - \max(\theta_L - \phi, c_f) - \frac{\Delta R(1-\eta)}{(\eta R - 1)(R-1)}\right]. \tag{5}$$

When $\theta_L < c_f$, in which case some Black- and white-owned firms do not apply for PPP, the disparity is negative at fintechs; Black-owned firms are, on average, more likely to be approved because of the selection of high-θ Black-owned firms into fintech. However, in the case where all Black-owned firms apply for PPP, i.e. $\theta_L - \phi > c_f$, there is a countervailing effect of Black-owned firms with particularly low approval probabilities applying to fintechs. This leads to a positive disparity at fintechs. Per our discussion in the prior section, the disparity at fintechs decreases with an increase in bank bias. This is consistent with our empirical findings.

At banks, the approval disparity, $A(w, b) - A(B, b)$ is:

$$\begin{aligned} A(w, b) - A(B, b) &= \frac{1}{2}\left[\theta_H + \frac{\Delta}{R-1}\right] - \frac{\eta}{2}\left[\theta_H - \phi + \frac{\Delta}{\eta R - 1}\right] \\ &= \frac{1}{2}\left[(1-\eta)(\theta_H - \phi) + \phi - \frac{\Delta(1-\eta)}{(\eta R - 1)(R-1)}\right] \end{aligned} \tag{6}$$

Unlike fintechs, banks will always fully internalize the disparity ϕ in approval probability distributions between white- and Black-owned firms. This is because they attract applications from firms with the highest approval probabilities, all of whom choose to apply for PPP. Also, per our previous discussion, bias η can either increase or decrease the bank approval disparity, depending on parameters.

Comparing the approval disparity at banks (6) with the approval disparity at fintechs (5), one can show that the disparities will only be equal if all firms choose to apply for PPP ($\theta_L - \phi > c_f$) and banks do not discriminate against Black applicants ($\eta = 1$). Given the sizable application disparities shown in Table 3 and the negative correlation of racial bias and Black-owned firms' approval rates at banks shown in Table 7, neither of these conditions appear to hold in the data.

When one or both of these conditions do not hold, the bank approval disparity will be strictly larger than the fintech approval disparity. To illustrate the intuition for this result, we first consider a case in which there is no bank bias ($\eta = 1$) but not all firms choose to apply for PPP loans ($c_f > \theta_L - \phi$), thus truncating the distribution of Black fintech applicants to those with $\theta > c_f$. With no discrimination, Black- and white owned firms use the same threshold probability for applying to banks: $\theta > \Delta/(R-1)$. The bank approval disparity will equal $\phi/2$, as it simply reflects the racial disparity in approval probability distributions absent any discrimination. However, because not all firms apply for PPP loans, the disparity in approval probability distributions ϕ means that a disproportionate share of low-θ Black-owned firms do not apply. These firms are therefore not included in fintech approval rates, which raises the mean θ of Black-fintech applicants and decreases the fintech approval disparity below $\phi/2$. Thus, while the lower cost of fintech applications induces more Black-owned firms to apply, the costs of applying still crowd out more low-θ Black-owned firms and thus reduce the fintech approval disparity. The same argument holds if there are also white-owned firms that do not apply for PPP loans, i.e., when $c_f > \theta_L$.

Now suppose that banks discriminate ($\eta < 1$). This makes it less appealing for Black-owned firms to apply to banks. It raises the threshold of θ above which Black-owned firms choose to apply to banks from $\Delta/(R-1)$ to $\Delta/(\eta R-1)$, thereby raising the mean θ of Black-owned firms that apply to fintechs and further reducing the approval disparity at fintechs relative to the case of $\eta = 1$ considered above. At the same time, discrimination increases the average θ of Black-owned firms that apply to banks. However, the effect on the average approval probability of Black-owned firms at banks is attenuated because discrimination lowers their approval probability. Thus, while selection due to bank discrimination tends to mitigate approval disparities at both banks and fintechs, the effect is more pronounced at fintechs. We conclude that selection effects tend to increase approval disparities at banks relative to fintechs.

Table A.1
Survey Representativeness: Industry Composition

This table compares the industry compositions of SBCS survey respondents and all firms nationally. The nationwide industry shares are derived from the Census' 2018 County Business Patterns and Nonemployer Statistics Combined Report. The eight industry categories are based on two-digit NAICS categories.

Industry Category	SBCS	Nationwide
Non-manufacturing goods production & associated services	15.36%	21.59%
Manufacturing	9.12%	1.88%
Retail	11.25%	9.19%
Leisure and hospitality	13.24%	8.31%
Finance and insurance	1.69%	3.59%
Healthcare and education	10.59%	11.34%
Professional services and real estate	23.35%	24.64%
Business support and consumer services	15.40%	19.47%

Table A.2
Definitions/Construction of SBCS-Derived Variables

This table describes the construction of all variables, other than industry categories, that we derive from the SBCS survey data. For the mapping between NAICS codes and SBCS industry categories see the "Definitions" section of any data appendix listed at https://www.fedsmallbusiness.org/survey. Table A.1 reports the share of firms in each industry category.

Variable/Term	SBCS Question(s)	Derivation/Definition
White-Owned business	You previously indicated that your business has number of owners owner(s). What is the race and ethnicity of the owner(s)? Please complete the entire table.	Dummy variable coded as 1 if: >= 50% equity held by owner(s) identifying as non-Hispanic white.
Black-Owned, Hispanic-Owned, Asian-Owned, Native-Owned, Middle Eastern or North African-Owned, Other-Owned, Woman-Owned business	""	Dummy variable coded as 1 if: >= 51% equity held by owner(s) identifying as (race/ethnicity/gender). Equity held by owners' identifying as multiple groups is counted toward totals for each included group.
Applied for PPP	(Q1) What type(s) of emergency assistance funding did your business seek? Select all that apply. (Q2) Why didn't your business apply for a PPP loan? Select all that apply. (Q3) How much PPP funding did your business apply for? Please input amount below. (Q4) Where did you apply for the PPP loan? Select all that apply	Dummy variable coded as 1 if: (Q1 = PPP OR Answered Q3 OR Answered Q4) AND ((Q1 = PPP OR Q1 Unanswered) AND Q2 Unanswered). Coded as 0 if: (Q1 Answered AND Q1 != PPP) OR Q2 Answered.
Lender types: Bank, Fintech, CU/CDFI	Where did you apply for the PPP loan? Select all that apply	Bank: Large OR Small bank. Fintech: Online/fintech lender OR Nonbank finance company OR Other lender. CU/CDFI: Credit Union OR Community development financial institution.
Applied for PPP at (Lender type)	""	Variable created directly from responses.
Received PPP	How much PPP funding did your business receive? Please input amount below.	Dummy variable coded as 1 if: Received > 0 funding. Coded as 0 if: Received 0 funding OR "Applied for PPP" = 0.
Received PPP at (Lender type)	At which source was your PPP loan application processed or most complete? Select one.	Dummy variable coded as 1 if: Received/most complete at (lender type) AND "Received PPP" = 1. Coded as 0 if "Applied for PPP = 0 OR "Received PPP" = 0 OR Received/most complete at different lender type.
Existing Relationship w/Lender (General)	Did your business have an existing relationship with the Source(s) from previous question prior to submitting your PPP loan application?	Dummy variable coded as 1 (0) if respondent reports relationship with at least one (no) lender type.
Existing Relationship w/(Lender type)	""	Dummy variable coded as 1 (0) if respondent reports relationship (no relationship) with (lender type).
# Owners + Employees	(Q1) How many owners does your business have? Only include those individuals who own a share of the business and/or profits (Q2) How many employees did your business have as of January 1, 2020, excluding owners? (Full-Time *only*)	Q1 + Q2 (Firms selecting "5 or more" owners are assumed to have five owners.)
Revenue categories	What were your business' total revenues in 2019? Please provide your best estimate.	Respondents choosing any category above $100k are grouped.
Profitability categories	At the end of 2019, was your business operating at a profit, break-even, or loss?	Variable created directly from responses.
Owner age categories	What is the age of the primary owner of this business?	"Under 25," "25-34," and "35-44" are grouped into the "<45" category; "45-54" and "55-64" are grouped into the "45-64" category; the "$\geq$ 65" category is created directly from the responses.
Employer Business	How many employees did your business have as of January 1, 2020, excluding owners? (Full- and Part-time)	Dummy variable coded as 1 if respondent reports at least one full- *or* part-time employee.
Uses Contract Workers	In the past 12 months, did your business use any contract workers?	Variable created directly from responses.

Figure A.1
Structure of the 2020 SBCS

This diagram illustrates the format of the 2020 SBCS. Blue sections are asked of all respondents. Red sections are asked of a subset of respondents based on their answers to certain questions in blue sections. Green sections are special topics modules asked of a subset of respondents opting to continue onto the special topics modules after the "Final Demographcis" section, based on their answers to certain question in blue sections. The yellow section is a special topics module asked of all respondents opting to continue onto the special topics modules. Note that there is additional "branching" *within* many sections, (e.g., follow-up questions contingent on certain responses).

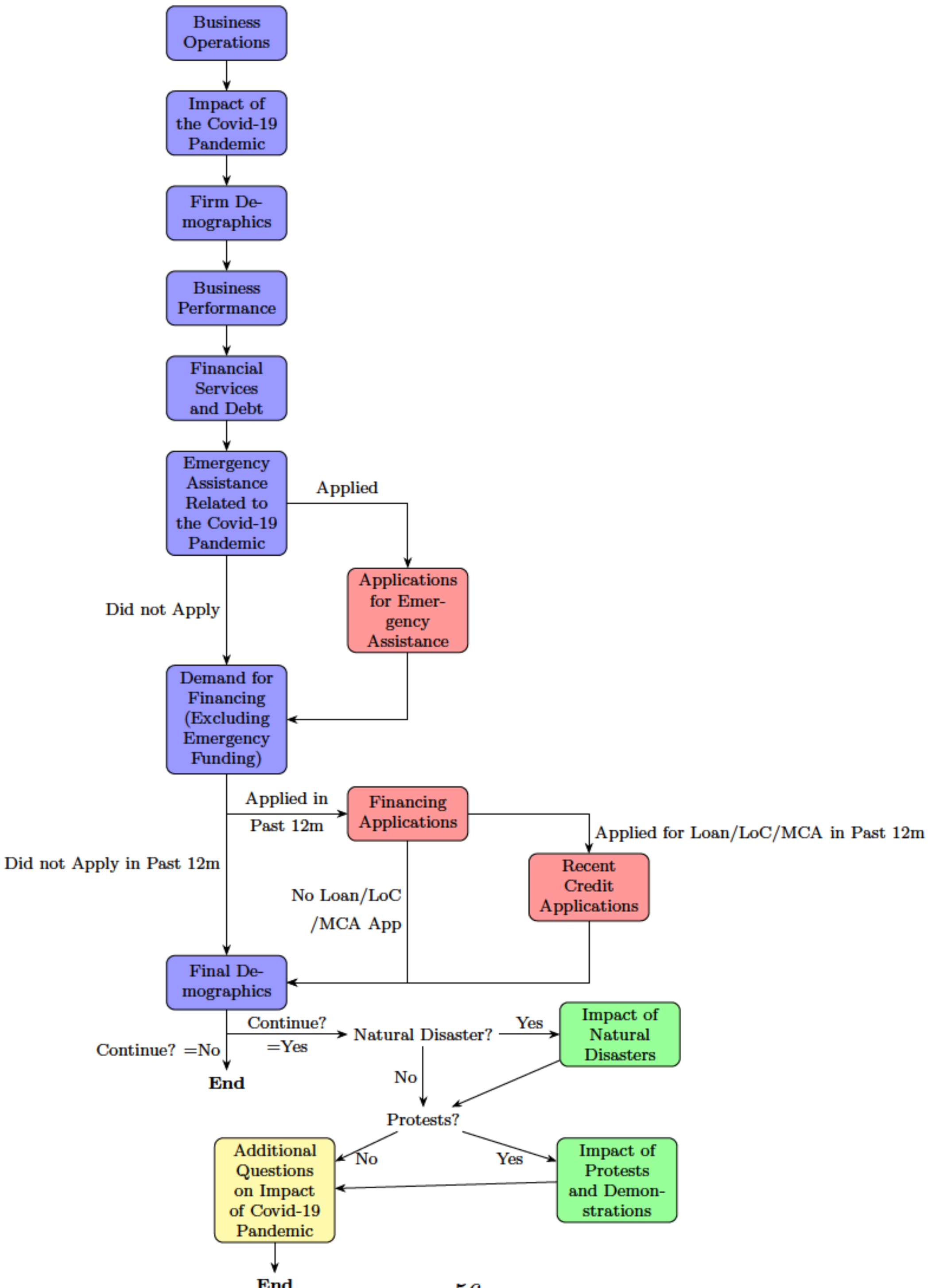
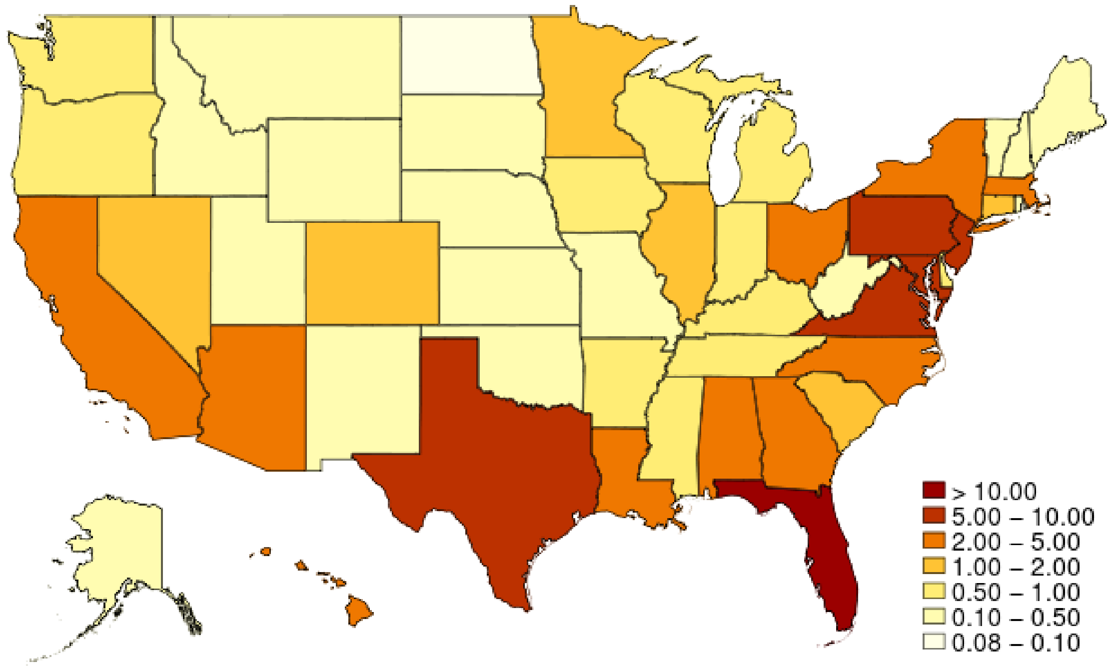


Figure A.2
Survey Representativeness: Geographic Distribution

The heat map in panel (a) shows each state's share of total respondents to the 2020 SBCS survey. The heat map in panel (b) shows each state's share of total U.S. establishments, per the Census' 2018 County Business Patterns and Nonemployer Statistics Combined Report.

(a) SBCS



(b) Census

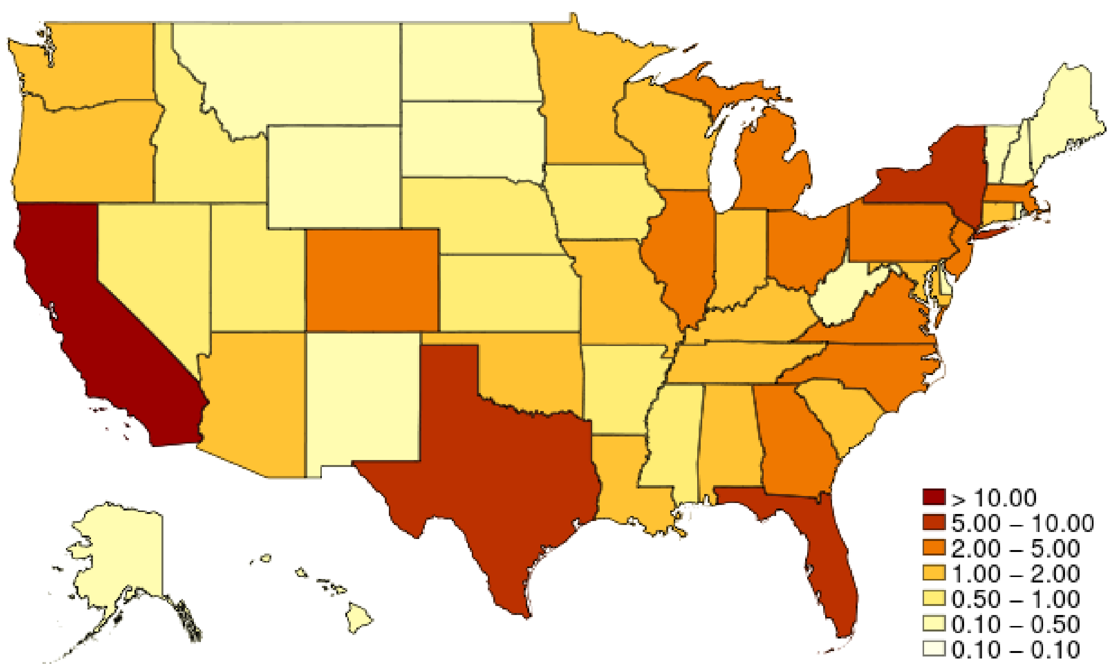
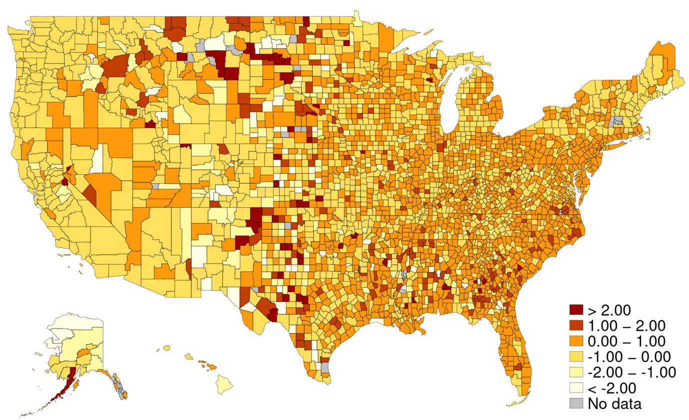


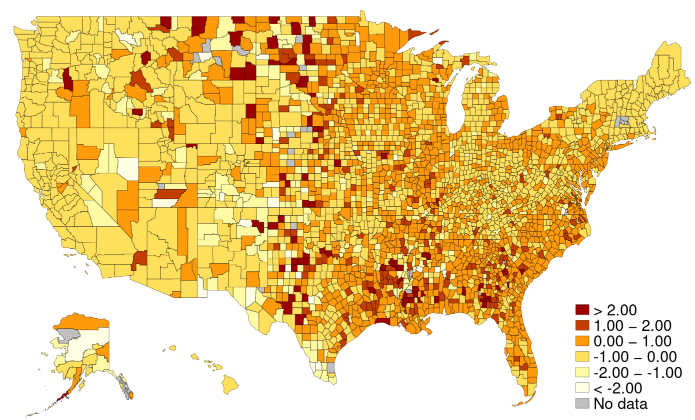
Figure A.3
IAT Distributions

The heat map in panel (a) shows the average implicit bias against Black people, measured as the average implicit preference for white people relative to Black people over all Black-white IAT tests taken by white people in a given county between 2008 and 2019. The heat map in panel (b) shows the average explicit bias against Black people in each county, measured as the average explicit preference for white people relative to Black people over all Black-white IAT tests taken by white people in a given county between 2008 and 2019. Implicit and explicit bias measures are standardized to have zero mean and unit variance. The heat map in panel (c) shows the total number of Black-white IAT tests taken by white people in each county between 2008 and 2019.

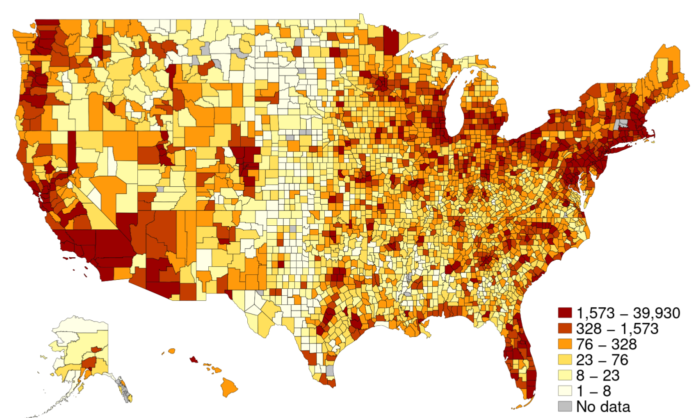
(a) Implicit Bias



(b) Explicit Bias



(c) Number of White Test-Takers



Internet Appendix

Applications or Approvals: What Drives Racial Disparities in the Paycheck Protection Program?

This internet appendix reports the following additional results:

1. Tables IA1 and IA2 report the results of the analyses of application behavior using an alternative sample that includes 292 firms that reported applying for PPP but did not report whether they received PPP funds.

2. Table IA3 reports the results of loan approval regressions while controlling for whether a firm has applied to other lender types.

3. Table IA4 reports the results of loan approval regressions that assume that all firms that applied only to a fintech lender but did not have an existing relationship with a fintech lender first tried applying to a bank and were rejected.

4. Tables IA5, IA6, and IA7 report the paper's main results, controlling for the personal credit score of the business owner. Specifically, Table IA5 reports the results of PPP application regressions, Table IA6 reports the results of bank versus fintech sorting regressions, and Table IA7 reports the results of approval regressions.

5. Tables IA8, IA9, and IA10 report the paper's main results, using analytical survey weights. Specifically, Table IA8 reports the results of weighted PPP application regressions, Table IA9 shows the results of weighted bank versus fintech sorting regressions, and Table IA10 displays the results of approval regressions.

6. Figure IA1 plots the shares of SBCS respondents in each state and industry against the analogous Census shares.

7. Figures IA2 and IA3 report the results of leave-one-state-out and leave-one-industry-out robustness checks for the main specifications.

Table IA1
Which Firms Apply for PPP? Alternative Sample

This table reports the results of linear probability model regressions of applying for a PPP loan using the empirical specifications in Tables 3 and 5. The samples differ because the results reported here include 292 firms that reported applying for PPP but did not report whether they received PPP funds. This sample also excludes 66 firms that did not provide information on current bank relationships. Robust standard errors are reported. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

				Lender type conditional on applying					
	All			Bank			Fintech		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black	−0.183***	−0.039***	−0.031**	−0.173***	−0.107***	−0.092***	0.149***	0.080***	0.075***
	(0.013)	(0.012)	(0.012)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)
Asian	0.048***	0.003	0.009	0.008	0.014	0.028*	0.011	−0.004	−0.009
	(0.015)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.016)	(0.015)
Hispanic	−0.051***	−0.038***	−0.033**	−0.045***	−0.011	−0.001	0.041***	0.003	−0.000
	(0.016)	(0.014)	(0.014)	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)
Female	−0.049***	0.024***	0.025***	−0.048***	−0.014	−0.012	0.039***	0.009	0.009
	(0.009)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Firm Characteristics									
Current Bank Relationship			0.110***			0.272***			−0.086***
			(0.010)			(0.014)			(0.013)
Log(Owners + Employees)		0.062***	0.058***		0.034***	0.026***		−0.029***	−0.026***
		(0.004)	(0.004)		(0.004)	(0.004)		(0.004)	(0.004)
Log(Years in Business)		0.000	−0.002		0.019***	0.015***		−0.012***	−0.011**
		(0.004)	(0.004)		(0.005)	(0.005)		(0.005)	(0.005)
\$25k-\$50k		0.109***	0.103***		0.013	0.018		0.017	0.015
		(0.019)	(0.019)		(0.036)	(0.035)		(0.036)	(0.035)
\$50k-\$100k		0.148***	0.137***		0.111***	0.090***		−0.096***	−0.089***
		(0.018)	(0.018)		(0.032)	(0.031)		(0.032)	(0.032)
More than \$100k		0.380***	0.362***		0.177***	0.153***		−0.151***	−0.143***
		(0.016)	(0.016)		(0.029)	(0.028)		(0.029)	(0.029)
Break-Even		−0.023	−0.024*		0.003	0.002		−0.011	−0.010
		(0.014)	(0.014)		(0.015)	(0.015)		(0.015)	(0.015)
Profit		0.001	0.000		0.004	0.004		−0.020*	−0.020*
		(0.011)	(0.011)		(0.012)	(0.012)		(0.012)	(0.012)
Owner Age 45-64		−0.035***	−0.035***		0.020*	0.019*		−0.021*	−0.020*
		(0.009)	(0.009)		(0.011)	(0.011)		(0.011)	(0.011)
Owner Age $\geq$ 65		−0.087***	−0.084***		0.036***	0.035***		−0.047***	−0.047***
		(0.012)	(0.012)		(0.013)	(0.013)		(0.013)	(0.013)
Employer Business		0.236***	0.235***		−0.033	−0.025		0.036	0.034
		(0.020)	(0.019)		(0.034)	(0.033)		(0.035)	(0.035)
Nonemployer × Break-Even		0.007	0.012		−0.053	−0.030		0.049	0.042
		(0.025)	(0.025)		(0.048)	(0.046)		(0.048)	(0.048)
Nonemployer × Profit		0.084***	0.088***		−0.059	−0.048		0.044	0.041
		(0.021)	(0.021)		(0.037)	(0.036)		(0.037)	(0.037)
Uses Contract Workers		−0.008	−0.010		−0.001	−0.002		0.018**	0.018**
		(0.007)	(0.007)		(0.008)	(0.008)		(0.008)	(0.008)
N	12,455	12,455	12,455	8,366	8,366	8,366	8,366	8,366	8,366
R^2	0.03	0.33	0.33	0.03	0.11	0.17	0.02	0.09	0.10
Mean of Dependent Variable	0.68	0.68	0.68	0.84	0.84	0.84	0.14	0.14	0.14
State FEs		✓	✓		✓	✓		✓	✓
Industry FEs		✓	✓		✓	✓		✓	✓
ZIP controls		✓	✓		✓	✓		✓	✓

Table IA2
Racial Bias and Application Behavior: Alternative Sample

This table reports the results of linear probability model regressions of applying for a PPP loan using the empirical specifications in Tables 3 and 5. The samples differ because the results reported here include 292 firms that reported applying for PPP but did not report whether they received PPP funds. Standard errors are clustered by county. Racial bias measures are standardized to have zero mean and unit variance. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

			Lender type conditional on applying			
	All		Bank		Fintech	
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.041***	−0.042***	−0.105***	−0.106***	0.077***	0.077***
	(0.012)	(0.012)	(0.017)	(0.017)	(0.017)	(0.016)
Black × Explicit Bias	−0.007		−0.106***		0.077**	
	(0.029)		(0.038)		(0.037)	
Black × Implicit Bias		0.018		−0.120**		0.097**
		(0.036)		(0.047)		(0.045)
N	12,499	12,499	8,383	8,383	8,383	8,383
R^2	0.33	0.33	0.11	0.11	0.09	0.09
Mean of Dependent Variable	0.68	0.68	0.84	0.84	0.15	0.15
State FEs	✓	✓	✓	✓	✓	✓
Industry FEs	✓	✓	✓	✓	✓	✓
Firm/ZIP Controls	✓	✓	✓	✓	✓	✓

Table IA3
Applying to Multiple Lender Types

This table reports the results of linear probability model regressions of receiving a PPP loan, conditional on applying. We follow the empirical specifications in Table 6, while adding a dummy variable for whether a firm has applied to other lender types. In columns 1–2 (3–4), the dependent variable is equal to one if the firm received a PPP loan from a bank (fintech). Robust standard errors are reported. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Bank		Fintech	
	(1)	(2)	(3)	(4)
Black	−0.089***	−0.058***	−0.191***	−0.099***
	(0.014)	(0.014)	(0.034)	(0.037)
Asian	0.010	0.015	0.030	0.028
	(0.009)	(0.010)	(0.037)	(0.040)
Hispanic	−0.024*	−0.020	−0.062	−0.042
	(0.013)	(0.013)	(0.040)	(0.042)
Female	−0.007	0.005	0.025	0.041*
	(0.006)	(0.006)	(0.024)	(0.025)
Applied to Other Lender Types	−0.556***	−0.535***	−0.465***	−0.496***
	(0.024)	(0.024)	(0.028)	(0.028)
Firm Characteristics				
Relationship w/Lender		−0.017*		0.029
		(0.009)		(0.024)
Log(Owners + Employees)		0.014***		0.015
		(0.003)		(0.015)
Log(Years in Business)		0.006		0.018
		(0.004)		(0.014)
$25k-$50k		0.009		0.008
		(0.040)		(0.062)
$50k-$100k		0.045		0.112*
		(0.034)		(0.059)
More than $100k		0.116***		0.219***
		(0.031)		(0.054)
Break-Even		−0.014		0.037
		(0.011)		(0.045)
Profit		−0.011		0.049
		(0.008)		(0.035)
Owner Age 45-64		0.006		−0.048
		(0.008)		(0.029)
Owner Age $\geq$ 65		−0.002		−0.082*
		(0.010)		(0.047)
Employer Business		0.229***		0.153**
		(0.043)		(0.074)
Nonemployer × Break-Even		0.129**		0.074
		(0.058)		(0.101)
Nonemployer × Profit		0.214***		0.178**
		(0.045)		(0.079)
Uses Contract Workers		−0.017***		0.018
		(0.006)		(0.024)
N	6,840	6,840	1,150	1,150
R^2	0.26	0.32	0.24	0.34
Mean of Dependent Variable	0.92	0.92	0.70	0.70
State FEs		✓		✓
Industry FEs		✓		✓
ZIP Controls		✓		✓

Table IA4
What if Banks Are Turning Away Firms at the Application Stage?

This table reports the results of linear probability model regressions of receiving a PPP loan from a bank, conditional on applying for a PPP loan. We assume that all firms that applied only to a fintech lender but did not have an existing relationship with a fintech lender first tried applying to a bank and were rejected. We also assume that they did not have an existing relationship with a bank. Following the empirical specifications in columns 3–4 of Table 6, we show that those results are robust to these alternative assumptions. Robust standard errors are reported. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)
Black	−0.200***	−0.100***
	(0.018)	(0.016)
Asian	0.005	0.023*
	(0.014)	(0.014)
Hispanic	−0.051***	−0.012
	(0.017)	(0.016)
Female	−0.033***	0.002
	(0.009)	(0.008)
Firm Characteristics		
Relationship w/Lender		0.346***
		(0.014)
Log(Owners + Employees)		0.024***
		(0.003)
Log(Years in Business)		0.012**
		(0.005)
$25k-$50k		0.017
		(0.038)
$50k-$100k		0.081**
		(0.033)
More than $100k		0.174***
		(0.030)
Break-Even		0.003
		(0.014)
Profit		0.010
		(0.011)
Owner Age 45-64		0.008
		(0.011)
Owner Age $\geq$ 65		0.010
		(0.013)
Employer Business		0.178***
		(0.040)
Nonemployer $\times$ Break-Even		0.059
		(0.054)
Nonemployer $\times$ Profit		0.163***
		(0.042)
Uses Contract Workers		−0.018**
		(0.007)
N	7,381	7,381
R^2	0.04	0.28
Mean of Dependent Variable	0.86	0.86
State FEs		✓
Industry FEs		✓
ZIP controls		✓

Table IA5
Which Firms Apply for PPP? Controlling for Credit Score

This table reports the results of linear probability model regressions of applying for a PPP loan. In order to match the sample used in Table 2, firms that report applying for PPP but do not report whether they received PPP funds are excluded from all regressions in the table. The dependent variable is equal to one if the firm applied for a PPP loan from any lender. Columns 1 and 2 report robust standard errors. In columns 3–4, standard errors are clustered by county. Racial bias measures are standardized to have zero mean and unit variance. All regressions include dummy variables for different bins of the owner's personal credit score. Firms that do not report a personal credit score have *Credit Score Missing* equal to one. The omitted group is below 620. The remaining firm controls include log owners plus employees, log years in business, revenues, profitability, owner age, an indicator for employer business, the interaction of a nonemployer indicator and profitability, and an indicator for use of contract workers. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)
Black	−0.047***	−0.046***	−0.047***	−0.037***
	(0.013)	(0.013)	(0.013)	(0.013)
Black × Explicit Bias		−0.011		
		(0.030)		
Black × Implicit Bias			0.014	
			(0.037)	
Asian	0.003	0.003	0.003	0.008
	(0.014)	(0.019)	(0.019)	(0.014)
Hispanic	−0.044***	−0.044***	−0.044***	−0.038***
	(0.014)	(0.015)	(0.015)	(0.014)
Female	0.023***	0.023***	0.023***	0.023***
	(0.007)	(0.008)	(0.008)	(0.007)
Select Firm Characteristics				
Current Bank Relationship				0.111***
				(0.010)
Credit Score Above 760	0.006	0.005	0.006	−0.006
	(0.018)	(0.018)	(0.018)	(0.018)
Credit Score 720-760	−0.007	−0.007	−0.007	−0.018
	(0.019)	(0.018)	(0.018)	(0.019)
Credit Score 680-719	−0.017	−0.017	−0.017	−0.026
	(0.020)	(0.020)	(0.020)	(0.020)
Credit Score 620-679	−0.032	−0.032	−0.031	−0.036*
	(0.022)	(0.021)	(0.021)	(0.022)
Credit Score Missing	−0.038**	−0.039**	−0.039**	−0.044**
	(0.019)	(0.018)	(0.018)	(0.019)
N	12,229	12,207	12,207	12,164
R^2	0.34	0.34	0.34	0.35
Mean of Dependent Variable	0.67	0.67	0.67	0.67
State FEs	✓	✓	✓	✓
Industry FEs	✓	✓	✓	✓
Firm/ZIP Controls	✓	✓	✓	✓

Table IA6
Where do Firms Apply for PPP? Controlling for Credit Score

This table reports the results of linear probability model regressions of applying for a PPP loan with a given lender type, within the sample of firms applying for PPP. As in Table 3, firms that report applying for PPP but do not report whether they received PPP funds are excluded from all regressions in the table. In columns 1–4 (5–8), the dependent variable is equal to one if the firm applied for a PPP loan from a bank (fintech). In columns 2–3 and 6–7, standard errors are clustered by county. In all other columns, robust standard errors are reported. Racial bias measures are standardized to have zero mean and unit variance. All regressions include dummy variables for different bins of the owner's personal credit score. Firms that do not report a personal credit score have *Credit Score Missing* equal to one. The omitted group is below 620. The remaining firm controls include log owners plus employees, log years in business, revenues, profitability, owner age, an indicator for employer business, the interaction of a nonemployer indicator and profitability, and an indicator for use of contract workers. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Applied to Bank				Applied to Fintech			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	−0.079***	−0.078***	−0.078***	−0.068***	0.053***	0.053***	0.052***	0.051***
	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.018)	(0.017)	(0.017)
Black × Explicit Bias		−0.090**				0.061		
		(0.039)				(0.039)		
Black × Implicit Bias			−0.107**				0.096**	
			(0.047)				(0.046)	
Asian	0.009	0.008	0.009	0.026*	0.004	0.005	0.004	−0.001
	(0.015)	(0.017)	(0.017)	(0.015)	(0.016)	(0.016)	(0.016)	(0.015)
Hispanic	−0.006	−0.003	−0.005	0.004	0.001	−0.002	0.000	−0.004
	(0.017)	(0.018)	(0.018)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Female	−0.014	−0.014	−0.013	−0.013	0.010	0.010	0.010	0.010
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Select Firm Characteristics								
Current Bank Relationship				0.269***				−0.080***
				(0.015)				(0.013)
Credit Score Above 760	0.121***	0.119***	0.120***	0.100***	−0.166***	−0.166***	−0.166***	−0.163***
	(0.026)	(0.028)	(0.028)	(0.025)	(0.027)	(0.027)	(0.027)	(0.027)
Credit Score 720-760	0.094***	0.092***	0.093***	0.079***	−0.150***	−0.149***	−0.150***	−0.148***
	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)	(0.025)	(0.025)	(0.027)
Credit Score 680-719	0.077***	0.075***	0.077***	0.064**	−0.132***	−0.132***	−0.132***	−0.130***
	(0.028)	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Credit Score 620-679	0.022	0.020	0.022	0.024	−0.066**	−0.066**	−0.066**	−0.071**
	(0.031)	(0.032)	(0.032)	(0.030)	(0.031)	(0.029)	(0.029)	(0.031)
Credit Score Missing	0.102***	0.101***	0.103***	0.094***	−0.160***	−0.159***	−0.160***	−0.159***
	(0.026)	(0.025)	(0.025)	(0.026)	(0.027)	(0.025)	(0.025)	(0.027)
N	8,187	8,170	8,170	8,154	8,187	8,170	8,170	8,154
R^2	0.11	0.11	0.11	0.18	0.10	0.10	0.10	0.11
Mean of Dependent Variable	0.84	0.84	0.84	0.84	0.14	0.14	0.14	0.14
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
Industry FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm/ZIP Controls	✓	✓	✓	✓	✓	✓	✓	✓

Table IA7
Which Firms Are Approved for PPP? Controlling for Credit Score

This table reports the results of linear probability model regressions of receiving a PPP loan, conditional on applying. In columns 1–3 (4–6), the sample consists of firms that applied for a PPP loan from a bank (fintech). In columns 2–3 and 6–7, standard errors are clustered by county. In all other columns, robust standard errors are reported. Racial bias measures are standardized to have zero mean and unit variance. All regressions include dummy variables for different bins of the owner's personal credit score. Firms that do not report a personal credit score have *Credit Score Missing* equal to one. The omitted group is below 620. The remaining firm controls include an indicator if the firm had a previous relationship with the lender type, log owners plus employees, log years in business, revenues, profitability, owner age, an indicator for employer business, the interaction of a nonemployer indicator and profitability, and an indicator for use of contract workers. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Bank			Fintech		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.058***	−0.058***	−0.058***	−0.077*	−0.075*	−0.078**
	(0.016)	(0.015)	(0.015)	(0.042)	(0.039)	(0.039)
Black × Explicit Bias		−0.067*			0.107	
		(0.039)			(0.099)	
Black × Implicit Bias			−0.089**			0.070
			(0.041)			(0.127)
Asian	0.016	0.015	0.015	0.053	0.053	0.055
	(0.012)	(0.013)	(0.013)	(0.050)	(0.052)	(0.052)
Hispanic	−0.016	−0.015	−0.016	−0.057	−0.064	−0.058
	(0.014)	(0.014)	(0.014)	(0.051)	(0.046)	(0.046)
Female	0.004	0.004	0.005	0.037	0.038	0.037
	(0.007)	(0.007)	(0.007)	(0.028)	(0.027)	(0.027)
Select Firm Characteristics						
Credit Score Above 760	0.132***	0.131***	0.131***	0.051	0.050	0.048
	(0.029)	(0.030)	(0.030)	(0.053)	(0.053)	(0.054)
Credit Score 720-760	0.132***	0.131***	0.132***	0.101*	0.099*	0.098*
	(0.030)	(0.030)	(0.030)	(0.055)	(0.058)	(0.058)
Credit Score 680-719	0.121***	0.120***	0.121***	0.078	0.081	0.077
	(0.031)	(0.029)	(0.029)	(0.058)	(0.061)	(0.062)
Credit Score 620-679	0.067*	0.066*	0.066**	0.075	0.074	0.074
	(0.034)	(0.034)	(0.034)	(0.058)	(0.052)	(0.052)
Credit Score Missing	0.137***	0.136***	0.137***	0.066	0.066	0.063
	(0.029)	(0.030)	(0.030)	(0.053)	(0.050)	(0.050)
N	6,840	6,824	6,824	1,150	1,150	1,150
R^2	0.12	0.12	0.12	0.12	0.12	0.12
Mean of Dependent Variable	0.92	0.92	0.92	0.70	0.70	0.70
State FEs	✓	✓	✓	✓	✓	✓
Industry FEs	✓	✓	✓	✓	✓	✓
Firm/ZIP Controls	✓	✓	✓	✓	✓	✓

Table IA8
Which Firms Apply for PPP? Weighted Regressions

This table reports the results of linear probability model weighted regressions of applying for a PPP loan. In order to match the sample used in Table 2, firms that report applying for PPP but do not report whether they received PPP funds are excluded from all regressions in the table. The dependent variable is equal to one if the firm applied for a PPP loan from any lender. All columns report robust standard errors. Racial bias measures are standardized to have zero mean and unit variance. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)
Black	−0.145***	−0.001	0.009
	(0.022)	(0.024)	(0.024)
Asian	0.094***	0.017	0.023
	(0.031)	(0.028)	(0.028)
Hispanic	−0.106***	−0.046	−0.041
	(0.030)	(0.029)	(0.028)
Female	−0.094***	−0.003	−0.003
	(0.016)	(0.015)	(0.015)
Firm Characteristics			
Current Bank Relationship			0.110***
			(0.016)
Log(Owners + Employees)		0.040***	0.036***
		(0.008)	(0.008)
Log(Years in Business)		−0.002	−0.005
		(0.008)	(0.008)
$25k-$50k		0.143***	0.133***
		(0.025)	(0.025)
$50k-$100k		0.157***	0.146***
		(0.025)	(0.025)
More than $100k		0.350***	0.334***
		(0.024)	(0.024)
Break-Even		−0.055**	−0.054**
		(0.024)	(0.023)
Profit		−0.018	−0.017
		(0.018)	(0.018)
Owner Age 45-64		−0.055***	−0.052***
		(0.018)	(0.018)
Owner Age $\geq$ 65		−0.123***	−0.114***
		(0.023)	(0.023)
Employer Business		0.362***	0.358***
		(0.028)	(0.028)
Uses Contract Workers		0.030**	0.025*
		(0.014)	(0.014)
Nonemployer × Break-Even		0.068**	0.069**
		(0.034)	(0.034)
Nonemployer × Profit		0.137***	0.140***
		(0.028)	(0.028)
N	11,579	11,579	11,519
R^2	0.03	0.29	0.30
Mean of Dependent Variable	0.46	0.46	0.46
State FEs		✓	✓
Industry FEs		✓	✓
ZIP controls		✓	✓

Table IA9
Where do Firms Apply for PPP? Weighted Regressions

This table reports the results of linear probability model weighted regressions of applying for a PPP loan with a given lender type, within the sample of firms applying for PPP. As in Table 3, firms that report applying for PPP but do not report whether they received PPP funds are excluded from all regressions in the table. In columns 1–3 (4–6), the dependent variable is equal to one if the firm applied for a PPP loan from a bank (fintech). Robust standard errors are reported in all columns. Racial bias measures are standardized to have zero mean and unit variance. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Applied to Bank			Applied to Fintech		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.261***	−0.197***	−0.186***	0.196***	0.121***	0.118***
	(0.039)	(0.041)	(0.038)	(0.038)	(0.041)	(0.040)
Asian	0.000	−0.001	0.034	0.010	0.016	−0.000
	(0.033)	(0.035)	(0.031)	(0.032)	(0.035)	(0.033)
Hispanic	−0.100**	−0.050	−0.012	0.099**	0.041	0.019
	(0.043)	(0.043)	(0.040)	(0.046)	(0.043)	(0.042)
Female	−0.073***	−0.022	−0.022	0.046**	0.004	0.005
	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.019)
Firm Characteristics						
Current Bank Relationship			0.307***			−0.131***
			(0.026)			(0.025)
Log(Owners + Employees)		0.049***	0.036***		−0.037***	−0.031***
		(0.007)	(0.007)		(0.008)	(0.007)
Log(Years in Business)		0.004	0.006		0.002	0.001
		(0.010)	(0.010)		(0.010)	(0.009)
$25k-$50k		−0.010	−0.002		−0.000	−0.008
		(0.055)	(0.050)		(0.053)	(0.051)
$50k-$100k		0.092*	0.062		−0.117**	−0.105**
		(0.050)	(0.046)		(0.048)	(0.046)
More than $100k		0.156***	0.122***		−0.157***	−0.143***
		(0.046)	(0.042)		(0.045)	(0.044)
Break-Even		0.047*	0.034		−0.057**	−0.045*
		(0.026)	(0.025)		(0.024)	(0.024)
Profit		0.038*	0.030		−0.046**	−0.038*
		(0.021)	(0.020)		(0.020)	(0.020)
Owner Age 45-64		0.003	−0.002		−0.027	−0.026
		(0.023)	(0.022)		(0.022)	(0.022)
Owner Age $\geq$ 65		0.035	0.030		−0.044	−0.041
		(0.030)	(0.029)		(0.029)	(0.029)
Employer Business		−0.083*	−0.074*		0.085*	0.076*
		(0.044)	(0.043)		(0.044)	(0.042)
Uses Contract Workers		0.027	0.022		0.018	0.020
		(0.018)	(0.017)		(0.017)	(0.017)
Nonemployer × Break-Even		−0.092	−0.064		0.091	0.071
		(0.058)	(0.055)		(0.058)	(0.056)
Nonemployer × Profit		−0.081*	−0.071		0.089**	0.082*
		(0.045)	(0.044)		(0.045)	(0.043)
N	7,831	7,831	7,801	7,831	7,831	7,801
R^2	0.04	0.13	0.20	0.03	0.11	0.12
Mean of Dependent Variable	0.78	0.78	0.78	0.20	0.20	0.19
State FEs		✓	✓		✓	✓
Industry FEs		✓	✓		✓	✓
ZIP controls		✓	✓		✓	✓

Table IA10
Which Firms Are Approved for PPP? Weighted Regressions

This table reports the results of linear probability model weighted regressions of receiving a PPP loan, conditional on applying. In columns 1–2 (3–4), the sample consists of firms that applied for a PPP loan from a bank (fintech). In columns 5–6, the dependent variable is equal to one if the firm received a PPP loan from any lender. Robust standard errors are reported. *ZIP controls* include the number of branches per-capita, log of population, log of median household income, white population share, and unemployment rate. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Bank		Fintech		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Black	−0.143***	−0.068	−0.236***	−0.201***	−0.234***	−0.143***
	(0.045)	(0.045)	(0.065)	(0.073)	(0.038)	(0.037)
Asian	0.023	0.016	0.046	0.069	0.010	0.012
	(0.027)	(0.027)	(0.079)	(0.078)	(0.025)	(0.025)
Hispanic	−0.105**	−0.102**	−0.083	−0.066	−0.094**	−0.075*
	(0.050)	(0.049)	(0.091)	(0.093)	(0.039)	(0.039)
Female	−0.042**	−0.001	0.064	0.048	−0.021	0.018
	(0.020)	(0.020)	(0.046)	(0.050)	(0.017)	(0.018)
Firm Characteristics						
Relationship w/Lender		−0.021		0.093*		0.023
		(0.025)		(0.048)		(0.020)
Log(Owners + Employees)		0.021***		−0.024		0.014**
		(0.007)		(0.035)		(0.006)
Log(Years in Business)		−0.000		0.020		0.008
		(0.009)		(0.025)		(0.009)
$25k-$50k		0.015		−0.012		0.041
		(0.065)		(0.096)		(0.050)
$50k-$100k		0.068		0.047		0.090*
		(0.059)		(0.091)		(0.047)
More than $100k		0.114**		0.017		0.116***
		(0.053)		(0.089)		(0.044)
Break-Even		−0.027		0.093		−0.003
		(0.017)		(0.077)		(0.017)
Profit		−0.019		0.073		0.011
		(0.014)		(0.067)		(0.014)
Owner Age 45-64		0.037		0.008		0.017
		(0.023)		(0.051)		(0.020)
Owner Age $\geq$ 65		−0.003		−0.168*		−0.032
		(0.031)		(0.090)		(0.028)
Employer Business		0.251***		0.203*		0.253***
		(0.054)		(0.111)		(0.047)
Uses Contract Workers		−0.019		0.010		0.002
		(0.017)		(0.046)		(0.015)
Nonemployer × Break-Even		0.129*		0.139		0.131**
		(0.072)		(0.142)		(0.059)
Nonemployer × Profit		0.232***		0.195*		0.212***
		(0.055)		(0.116)		(0.048)
N	6,565	6,565	1,073	1,073	7,774	7,774
R^2	0.03	0.14	0.03	0.19	0.04	0.17
Mean of Dependent Variable	0.87	0.87	0.70	0.70	0.88	0.88
State FEs		✓		✓		✓
Industry FEs		✓		✓		✓
ZIP controls		✓		✓		✓

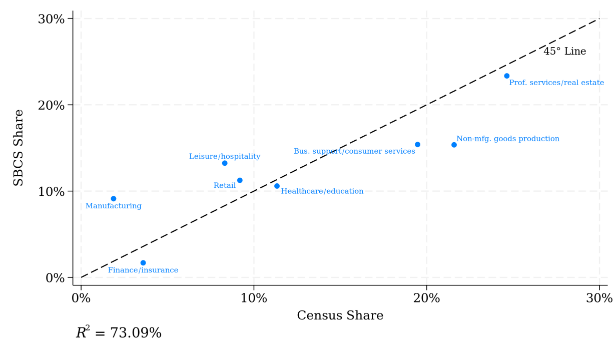
Figure IA1

Survey Representativeness: State, Industry Category, and Sector

This figure plots the SBCS share and nationwide share of firms in a given state (panel (a)), industry category (panel (b)), and NAICS sector (panel (c)). The nationwide shares are calculated using total U.S. establishments from the Census' 2018 County Business Patterns and Nonemployer Statistics Combined Report. Each panel includes a 45° line and reports the R^2 from a simple linear regression of the SBCS share on the nationwide share.

(a) State

(b) Industry Category



(c) NAICS Sector

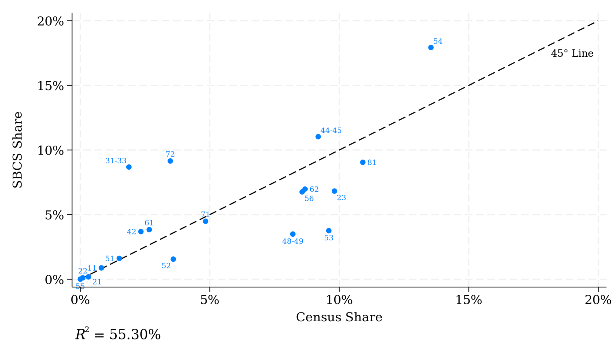


Figure IA2
Leave-One-Out: States

This figure shows the results for leave-one-out robustness checks for various specifications. Panel (a) mirrors the uptake specification in column 2 of Table 2. Panel (b) mirrors the application specification in column 2 of Table 3. Panel (c) mirrors the sorting to banks specification in column 2 of Table 5. Panels (d) and (e) mirror the approval specifications to banks and fintechs in columns 2 and 4 of Table 6, respectively. The plots show the point estimates and 95% confidence intervals (computed from robust standard errors) for the *Black* coefficient from dropping all firms in the indicated state from the sample. If dropping a particular state would result in less than 50 observations being removed from the sample, we do not report estimates.

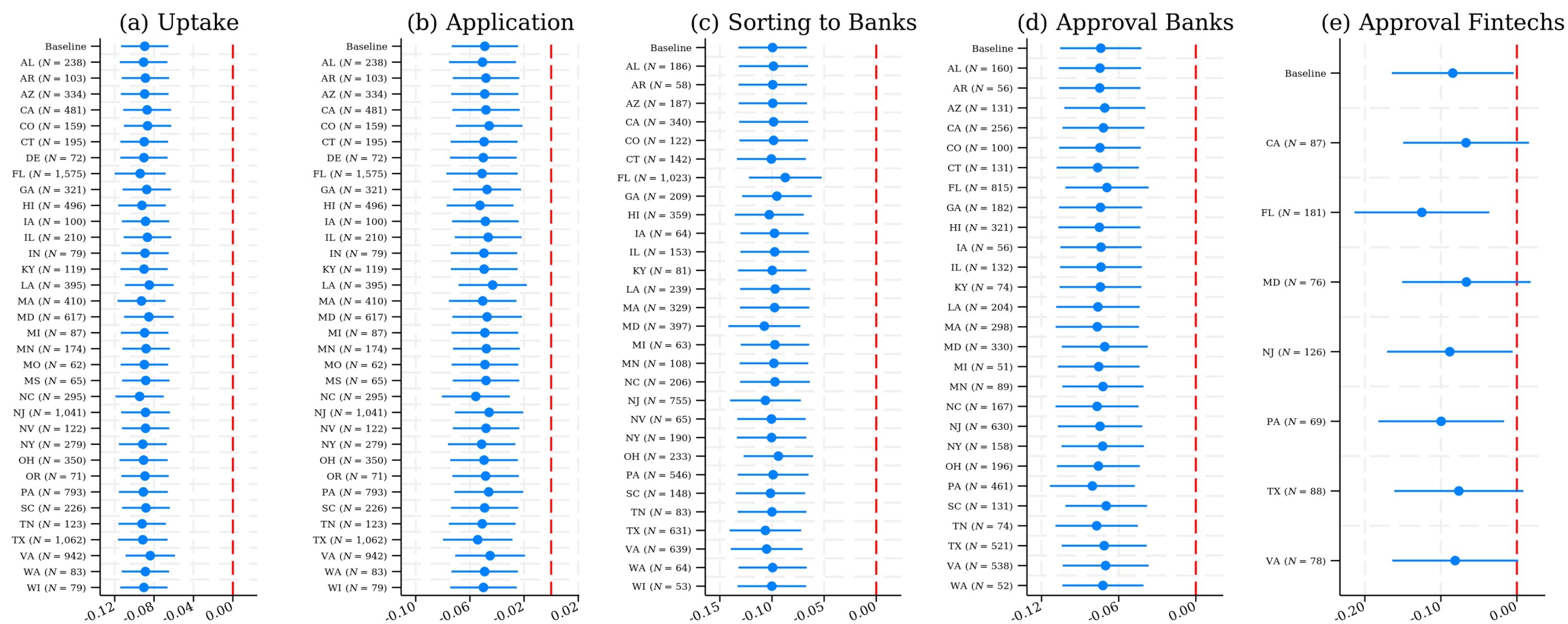


Figure IA3
Leave-One-Out: Industry Categories

This figure shows the results for leave-one-out robustness checks for various specifications. Panel (a) mirrors the uptake specification in column 2 of Table 2. Panel (b) mirrors the application specification in column 2 of Table 3. Panel (c) mirrors the sorting to banks specification in column 2 of Table 5. Panels (d) and (e) mirror the approval specifications to banks and fintechs in columns 2 and 4 of Table 6, respectively. The plots show the point estimates and 95% confidence intervals (computed from robust standard errors) for the Black coefficient from dropping all firms in the indicated industry category from the sample. The number of firms dropped from a given industry category is indicated in parenthesis. If dropping a particular industry category would result in less than 50 observations being removed from the sample, we do not report estimates. This only occurs for the Finance and insurance industry category in panel (e).