Which lenders had the highest minority share among their Payment Protection Program (PPP) loans?

Sabrina T. Howell, Theresa Kuchler, Johannes Stroebel*

This version: December 10, 2020

I Introduction

The economic crisis induced by the COVID-19 pandemic was devastating for small businesses in the United States, and minority-owned small businesses closed at much higher rates than White-owned businesses (Greenwood et al., 2020; Bartik et al., 2020; Fairlie, 2020; Alekseev et al., 2020). In March 2020, the U.S. Congress responded with provisions in the CARES Act that authorized $650 billion in Payment Protection Program (PPP) loans to small businesses. While guaranteed by the government, PPP loans were processed and disbursed by private lenders. Section 1102 of the CARES Act explicitly specified that the program should prioritize "small business concerns owned and controlled by socially and economically disadvantaged individuals."[1] However, the SBA did not issue specific guidance for distributing the loans, leaving private financial institutions administering the loans to independently determine which businesses to serve first or at all. Quickly, media reports raised concerns that minority-owned businesses struggled to access PPP loans (Zhou, 2020; Beer, 2020).

This short research note explores how PPP lenders differed in the share of their loans that went to minority-owned and especially to Black-owned businesses. Answering this question is challenging, since owner race was not systematically reported in PPP applications to the SBA. We employ data newly released by the SBA on December 1, 2020, which include the names of all 5.16 million PPP borrowers.[2] For self-employed individuals and sole proprietorships, the business name often corresponds to the name of the owner, allowing us to build on a well-established literature that predicts race given a person's name and location (Imai and Khanna,

*All authors are at NYU Stern. Preliminary analysis, final numbers subject to change. Please contact Howell at Sabrina.howell@nyu.edu or 917-519-8052 with questions. We are grateful to Georgij Alekseev and Jun Wong for superb research assistance. Howell's work on this project is funded by the Kauffman Foundation.

[1] A similar desire for PPP loans to reach underserved communities was expressed in the December 2020 Framework for a *Bipartisan Emergency COVID Relief Act* (2020), a bi-partisan proposal for further COVID relief.

[2] The newly released SBA data contains 4,837 unique institutions who participated as lenders in the PPP program. Together, they gave out 5,156,850 PPP loans with SBA approval dates between April 3 and August 8, with a hiatus from April 17 until April 26. During that period the first round of funding ran out, and Congress had not yet appropriated the second round.

2016; Humphries et al., 2019; Tzioumis, 2018). Using a random forest algorithm, we enhance the accuracy of these predictions by training our model on a subset of PPP borrowers who self-reported race. We document substantial variation across types of financial institutions in the propensity to lend to minority-owned businesses, a finding that is robust to alternative proxies for which business is minority-owned. Our results suggest that fintech lenders appear to have played an important role in extending PPP loans to Black- and Hispanic-owned businesses.

II PPP Loan Characteristics by Lender Type

We categorize the set of PPP lenders into one of 13 mutually exclusive groups. We include each of the top four banks by assets separately: JP Morgan Chase, Bank of America, Wells Fargo, and Citibank. The next category is large banks, which we define as those with more than $100 billion in assets, excluding the four largest banks. We then split the remaining banks by the median asset value to create a medium bank category with more than $2.2 billion in assets and a small bank category with less than $2.2 billion in assets. The remaining categories are credit unions, Business Development Corporations (BDCs), Minority Development Institutions (MDIs), Community Development Financial Institutions (CDFIs), nonprofits, and fintech lenders.[3]

Table 1: Loan Summary Statistics by Lender Type

	Number Lenders	Number Loans (100k)	Total Amt Lent (Bill)	Mean Loan Amt	Median Loan Amt	Share Loans < $\$22,880$ (Median)
All	4,837	5,156.850	522.950	101,409	22,880	50%
Bank of America	1	343.400	25.527	74,336	20,833	53%
Citibank	1	30.845	3.384	109,716	30,300	42%
JPMC Bank	1	280.160	29.348	104,754	28,740	43%
Wells Fargo Bank	1	194.291	10.529	54,190	18,979	59%
Bus Dev Corp	3	6.717	0.466	69,413	20,800	55%
Large Banks (assets>$130b ex top 4)	16	550.698	79.237	143,884	32,500	41%
Medium Banks ($2b<assets<$130b)	507	1,296.648	189.205	145,919	35,390	39%
Small Banks (<$2b assets)	3,087	1,256.745	130.709	104,006	27,500	45%
Credit Union	927	208.099	9.841	47,288	16,452	64%
Community Dev Fin Inst	129	77.568	6.311	81,364	20,833	52%
Minority Dev Inst	110	141.459	10.772	76,148	20,800	57%
Nonprofit	30	13.083	0.638	48,738	20,800	57%
Fintech	24	757.137	26.984	35,640	15,000	76%

Table 1 shows loan summary statistics by lender type. Small and medium banks accounted for roughly half of all loans with median loan values of $27,500 and $35,390, respectively. The larger banks made the majority of the remaining loans. Fintechs made 757,137 loans with a median value of $15,000. CDFIs, MDIs, and nonprofits jointly made 232,110 loans, with

[3]We include in the fintech category the lenders officially designated by the SBA as fintechs as well as online lenders that we know originate primarily for or via fintech partners or platforms, online lenders founded since 2005, and online lenders that received venture capital (VC) investment. The single largest fintech by loan volume is Cross River, a bank. However, they originated an overwhelming quantity of loans for fintech partners such as Kabbage, were founded in 2008, and they received VC.

median values of around \$21,000 each. Therefore, fintech lenders originated much smaller loans than other lenders, suggesting they served smaller firms on average.

III Methodology

To explore lending differences across types of financial institutions, we run the following regression at the level of the individual loan recipient for several racial categories, with a focus on Black-owned businesses:

$$Black_i = \beta LenderType_i + \alpha_{City} + \alpha_{State} + \alpha_{Industry} + \alpha_{LoanAmountPctile} + \varepsilon_i \tag{1}$$

Lender type includes indicators for each of the 13 lender type groups. With no controls, the estimates reflect the unconditional share of loans to Black-owned businesses by lender type. In some specifications, we also include dummy variables to account for the role of location (captured by the borrower's city), industry (captured by NAICS 3-digit industry classification, including categories such as "Health and Personal Care Stores," "Truck Transportation," and "Food Services and Drinking Places"), and loan size (captured by indicators for loan amount percentiles).

Whether a business is minority-owned is reported for a small subset of PPP borrowers who choose to self-identify their race in the loan application, and for which the lender also chose to report this information to the SBA. For our primary measure, we therefore build on a well-established literature that predicts race given a person's name for all borrowers for whom the data contains the owner's name (a substantial fraction of self-employed individuals and sole proprietorships). Specifically, we create two random forest models to predict race. The first model is based only on the first and last names of a business owner wherever this is available. The first name is matched with a list of first names as in Tzioumis (2018) and the last name is matched with a list of surnames as in Imai and Khanna (2016). We input the race distributions for both names into the random forest model and train the model on the subset of the self-employed/sole proprietor sample where race is self-identified. Afterward, we validate the model on the remainder of these businesses before applying it to the full sample. The second random forest model starts with the same two inputs and enhances the prediction by adding Bayesian posterior probabilities from combining the first name with the business location (Imai and Khanna, 2016). Both of these models provide us with a probbility that each loan is to a minority-owned business.[4]

IV Results

Figure 1 shows preliminary estimates using our preferred predictor of Black ownership within the subset of self-employed/sole proprietor firms for which information on owner name allows us to predict race. Panel A shows the share of loans for each lender that went to a business that

[4]We are working on expanding these models to allow us to generate predicted race more accurately and for a larger set of borrowers.

is predicted to be Black-owned. Panel B includes controls for business location, industry, and loan amount, and reflects the shares of loans for each lender type to Black-owned businesses not explained by these factors. Both panels show that fintechs, MDIs, and nonprofits tend to make a substantially larger share of their PPP loans to Black-owned businesses. Small- and medium-sized banks are consistently least likely to lend to Black-owned businesses, with large banks close behind.

We find similar patterns when using alternative measures of identifying loans to minority-owned businesses. Specifially, we find the same results using a prediction algorithm that does not incorporate firm location (Figure A.1), when using an alternative cutoff for predicting Black (Figure A.2), and when using only those PPP loans that the lender reports as self-identifying as Black-owned (Figure A.3).

A similar pattern emerges at the community level in Figure 2, where we analyze the share of the population that is Black in the zip codes of PPP borrowers, using all PPP loans to all firms (the SBA data includes firm location for all firms). Fintechs, CFDIs, MDIs, and nonprofits made a larger share of their loans in ZIP codes with a higher share of black residents.

We explore differences in lending to Hispanic- and Asian-owned businesses in Figures 3 and 4. Lending to Hispanic-owned businesses exhibits similar patterns as lending to Black-owned businesses. Lending to Asian-owned businesses shows markedly different patterns. MDIs are most likely to lend to Asian-owned businesses, followed by some of the largest banks.

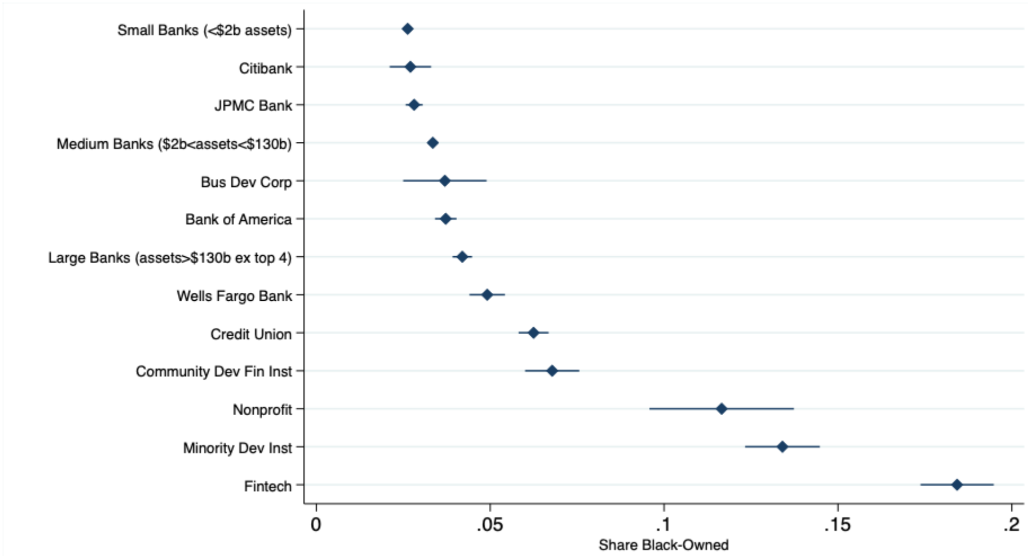
Overall, we find that, relative to other lenders, MDIs, nonprofits, and fintech lenders make a substantially larger share of their loans to minority borrowers, particularly Black- and Hispanic-owned businesses. While nonprofits made a high share of their loans to minorities, they made a very small number of total PPP loans (13,000). Fintech lenders, therefore, appear to have played an important role in extending PPP loans to Black- and Hispanic-owned businesses.

Importantly, these results thus do not necessarily indicate discriminatory lending practices by some lenders. In particular, the observed patterns could, among other things, reflect higher demand from Black and Hispanic business owners for fintech loans. Alternatively, traditional lenders may have lent at lower rates to Black or Hispanic businesses because they prioritized customers who were less likely to be Black or Hispanic (for example, because they had no pre-existing business relationship with these borrowers).[5] In ongoing work with data from Ocrolus, Lendio, and Middesk, we hope to shed more light on mechanisms. For example, we are linking business checking account data to the PPP lending data to explore the role of pre-existing customer relationships with different types of financial institutions.

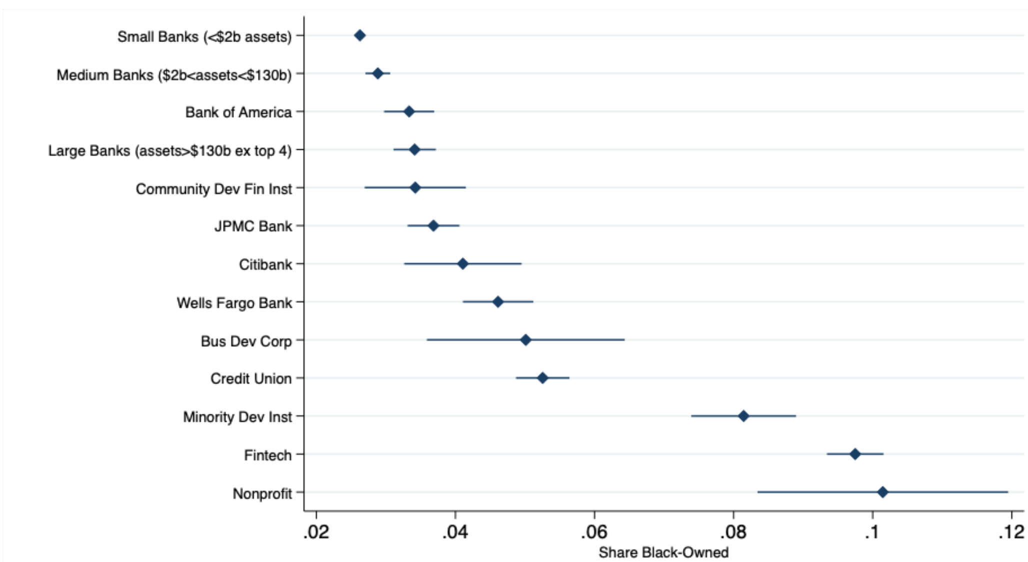
[5]For loan applications below $350,000, which includes the vast majority of applications, lenders were incentivized to prioritize larger loans since they receive a fee of 5% of the loan value. Since banks also have an incentive to keep their existing borrowers in good financial health, they also have an incentive to prioritize their clients with existing credit relationships (Granja et al., 2020).

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

A: No Controls



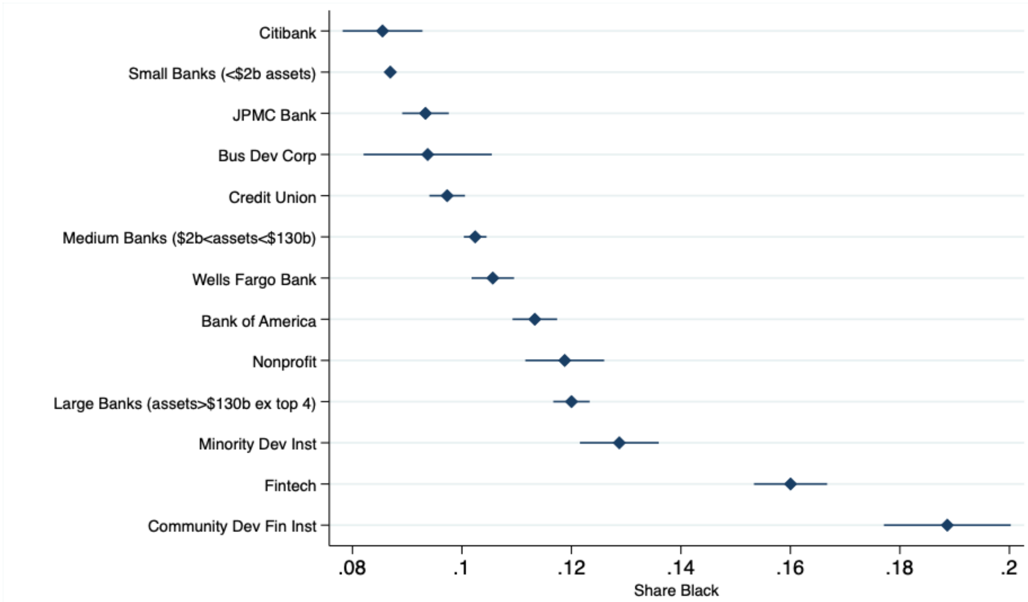
B: Full Controls



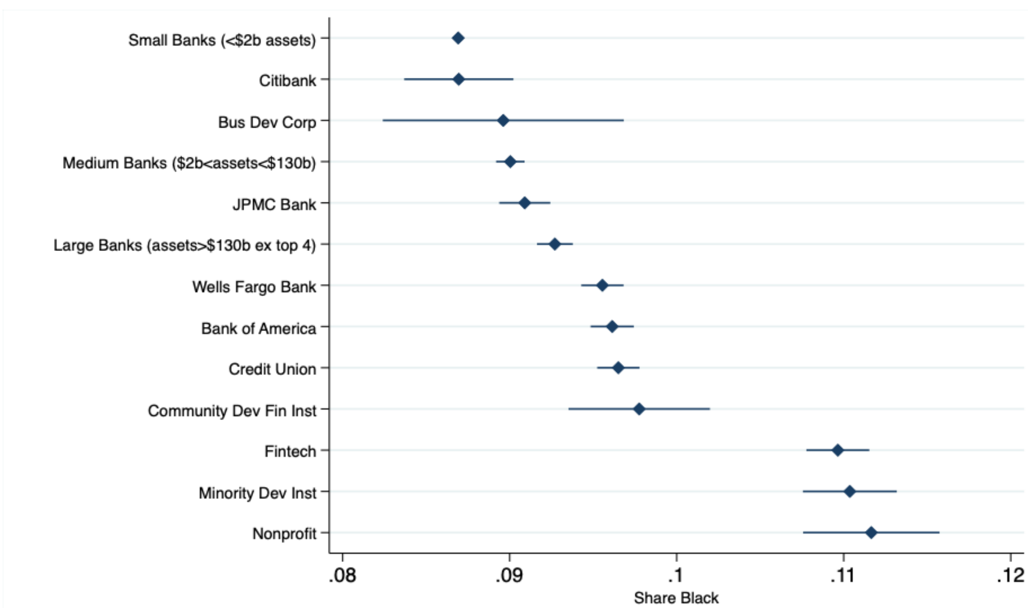
Note: This figure shows shares of PPP loans made to businesses predicted to be Black-owned by lender type. We classify businesses as Black-owned if our algorithm predicts a probability of Black ownership of over 50% based on the name and gender of the business owner and the business location. Included in the sample are loans to self-employed individuals and sole proprietorships for which we observe business owner name in the data. Each graph presents coefficients from a regression of equation 1, where we add back the mean of the dependent variable among the excluded lender category. The dependent variable is an indicator for whether the business is Black-owned, and the independent variables are indicators for mutually exclusive categories for PPP lender type with small banks as the base category. The bottom graph includes fixed effects for borrower city, state, and NAICS3 industry, and loam amount percentiles. Standard errors are clustered by zip code.

Figure 2: **Share of Black Population in Businesses' Communities by Institution Type**

A: No Controls



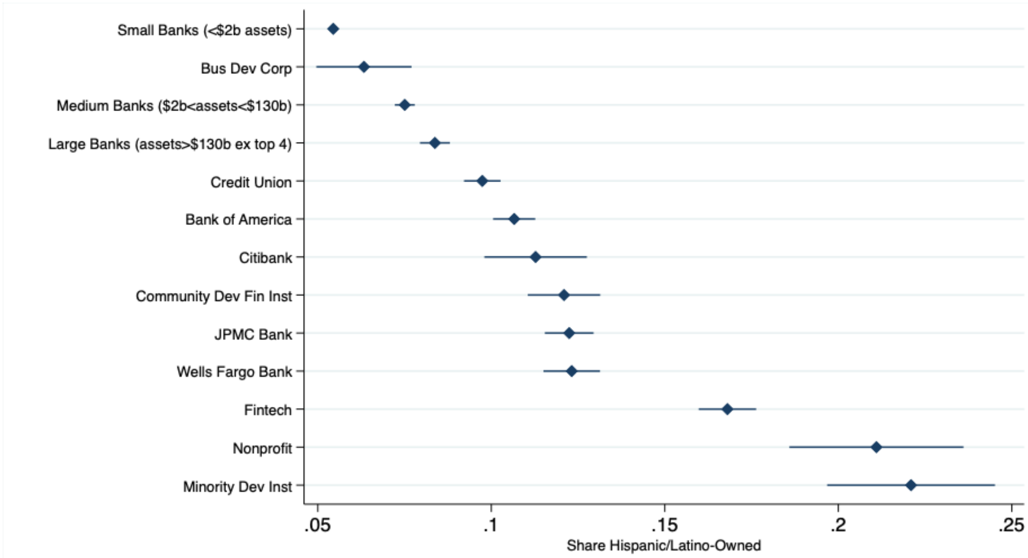
B: Full Controls



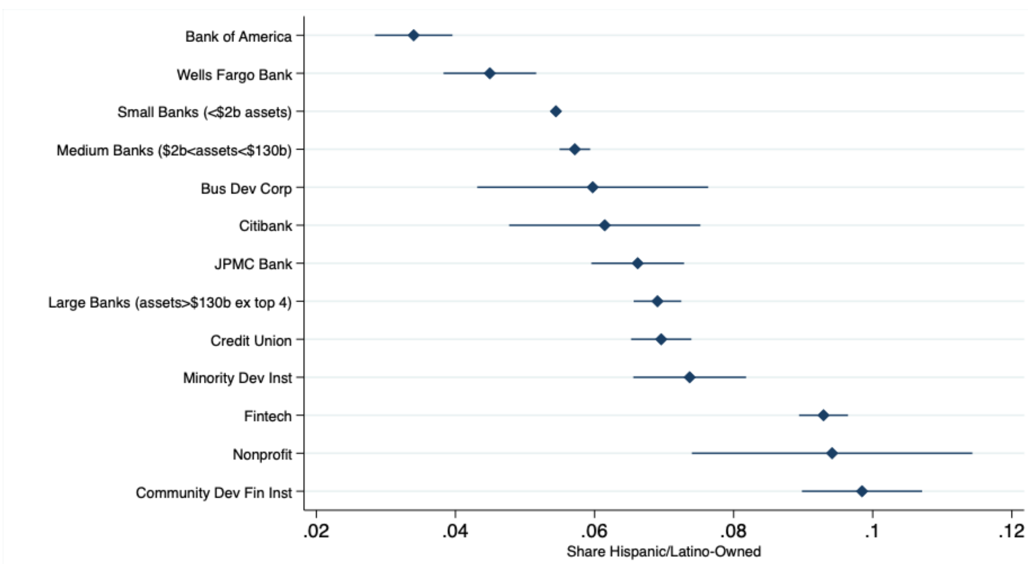
Note: This figure shows the share of Black residents in the ZIP codes of PPP loan recipients by lender type. Each graph presents coefficients from a regression of equation 1, where we add back the mean of the dependent variable among the excluded lender category. The dependent variable is the share of the zip code's population that is Black, and the independent variables are indicators for mutually exclusive categories for PPP lender type with small banks as the base category. The bottom graph includes fixed effects for borrower city, state, and NAICS3 industry, and loam amount percentiles. Standard errors are clustered by zip code.

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

A: No Controls



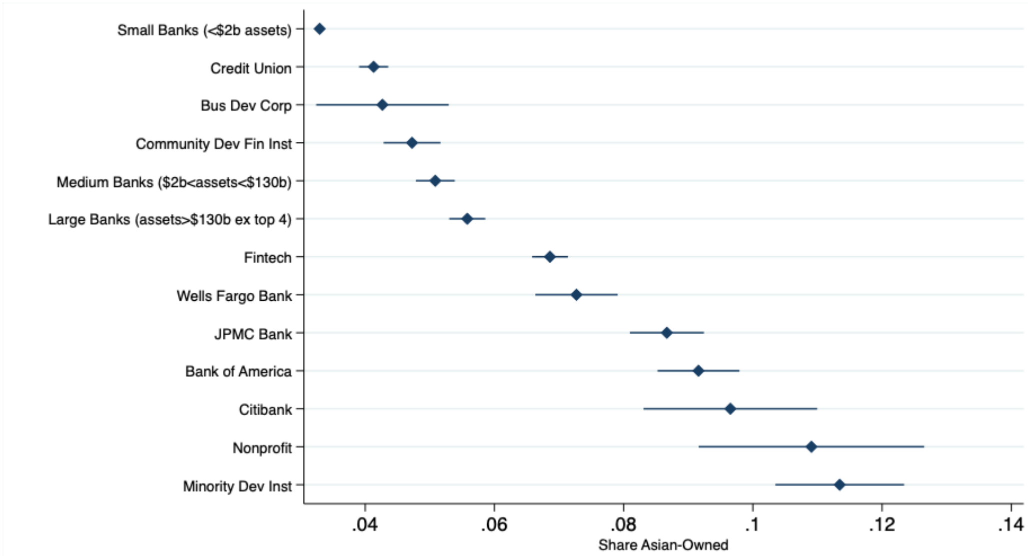
B: Full Controls



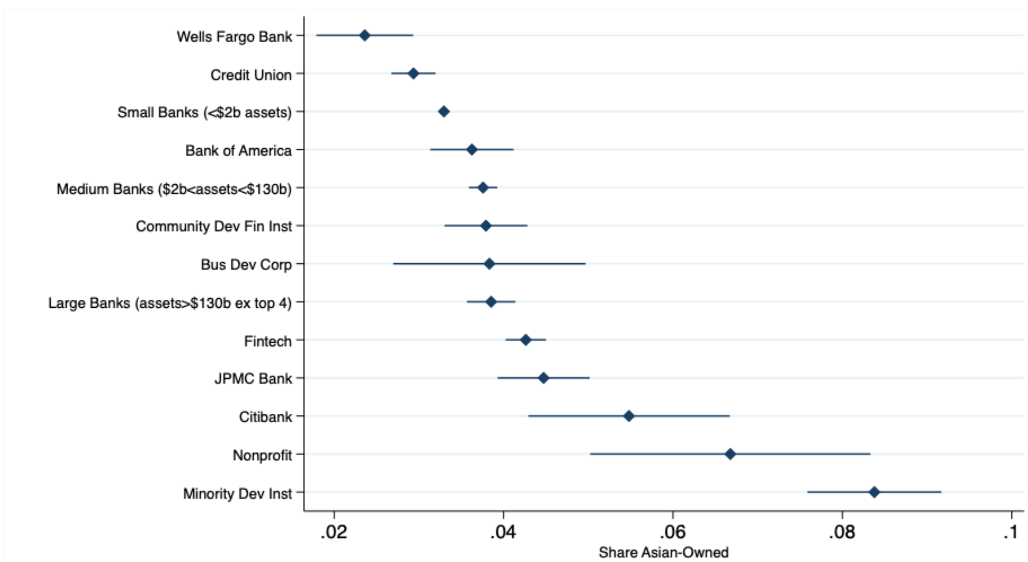
Note: This figure shows shares of PPP loans made to businesses predicted to be Hispanic-owned by lender type. We classify businesses as Hispanic-owned if our algorithm predicts a probability of Hispanic ownership of over 50% based on the name and gender of the business owner and the business location. Included in the sample are loans to self-employed individuals and sole proprietorships for which we observe business owner name in the data. Each graph presents coefficients from a regression of equation 1, where we add back the mean of the dependent variable among the excluded lender category. The dependent variable is an indicator for whether the business is Hispanic-owned, and the independent variables are indicators for mutually exclusive categories for PPP lender type with small banks as the base category. The bottom graph includes fixed effects for borrower city, state, and NAICS3 industry, and loam amount percentiles. Standard errors are clustered by zip code.

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

A: No Controls



B: Full Controls



Note: This figure shows shares of PPP loans made to businesses predicted to be Asian-owned by lender type. We classify businesses as Asian-owned if our algorithm predicts a probability of Asian ownership of over 50% based on the name and gender of the business owner and the business location. Included in the sample are loans to self-employed individuals and sole proprietorships for which we observe business owner name in the data. Each graph presents coefficients from a regression of equation 1, where we add back the mean of the dependent variable among the excluded lender category. The dependent variable is an indicator for whether the business is Asian-owned, and the independent variables are indicators for mutually exclusive categories for PPP lender type with small banks as the base category. The bottom graph includes fixed effects for borrower city, state, and NAICS3 industry, and loam amount percentiles. Standard errors are clustered by zip code.

References

Alekseev, G., S. Amer, M. Gopal, T. Kuchler, J. W. Schneider, J. Stroebel, and N. Wernerfelt, "The Effects of COVID-19 on US Small Businesses: Evidence from Owners, Managers, and Employees," Technical Report, NBER Working Paper No. w27833 2020.

Bartik, Alexander W, Marianne Bertrand, Zoe Cullen, Edward L Glaeser, Michael Luca, and Christopher Stanton, "The impact of COVID-19 on small business outcomes and expectations," *Proceedings of the National Academy of Sciences*, 2020, *117* (30), 17656–17666.

Beer, Tommy, "Minority-Owned Small Businesses Struggle To Gain Equal Access To PPP Loan Money," https://www.forbes.com/sites/tommybeer/2020/05/18/minority-owned-small-businesses-struggle-to-gain-equal-access-to-ppp-loan-money/?sh=66237cd05de3 2020. [Online; accessed 09-Dec-2020].

Bipartisan Emergency COVID Relief Act

***Bipartisan Emergency COVID Relief Act**, https://assets.documentcloud.org/documents/20421761/12920-emergency-covid-relief-act-of-2020-framework-summary.pdf 2020. [Online; accessed 09-Dec-2020].*

Fairlie, R., *"The impact of COVID-19 on small business owners: Evidence from the first three months after widespread social-distancing restrictions," Journal of Economics & Management Strategy, 2020, 29, 727–740.*

Granja, J., C. Makridis, C. Yannelis, and E. Zwick, *"Did the Paycheck Protection Program Hit the Target?," Technical Report, NBER Working Paper No. w27095. 2020.*

Greenwood, Robin M, Benjamin Charles Iverson, and David Thesmar, *"Sizing up corporate restructuring in the covid crisis," NBER Working Paper, 2020, (w28104).*

Humphries, J. E., N. Mader, D. Tannenbaum, and W van Dijk, *"Does eviction cause poverty? quasi-experimental evidence from Cook County, IL.," Technical Report, NBER Working Paper No. w26139 2019.*

Imai, K. and K. Khanna, *"Improving ecological inference by predicting individual ethnicity from voter registration records," Political Analysis, 2016, pp. 263–272.*

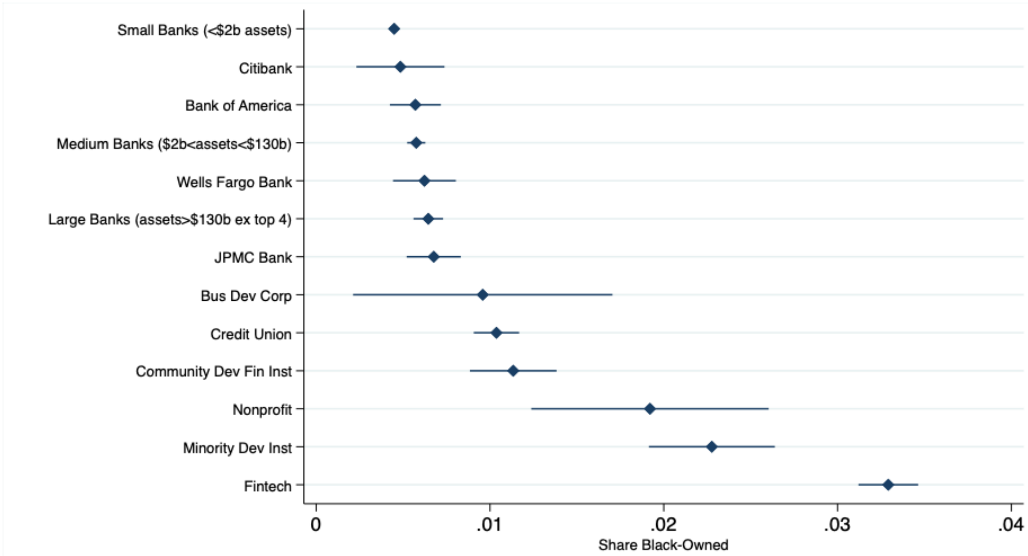
Tzioumis, Konstantinos, *"Demographic aspects of first names," Scientific data, 2018, 5, 180025.*

Zhou, Li, *"The Paycheck Protection Program failed many Black-owned businesses," https://www.vox.com/2020/10/5/21427881/paycheck-protection-program-black-owned-businesses 2020. [Online; accessed 09-Dec-2020].*

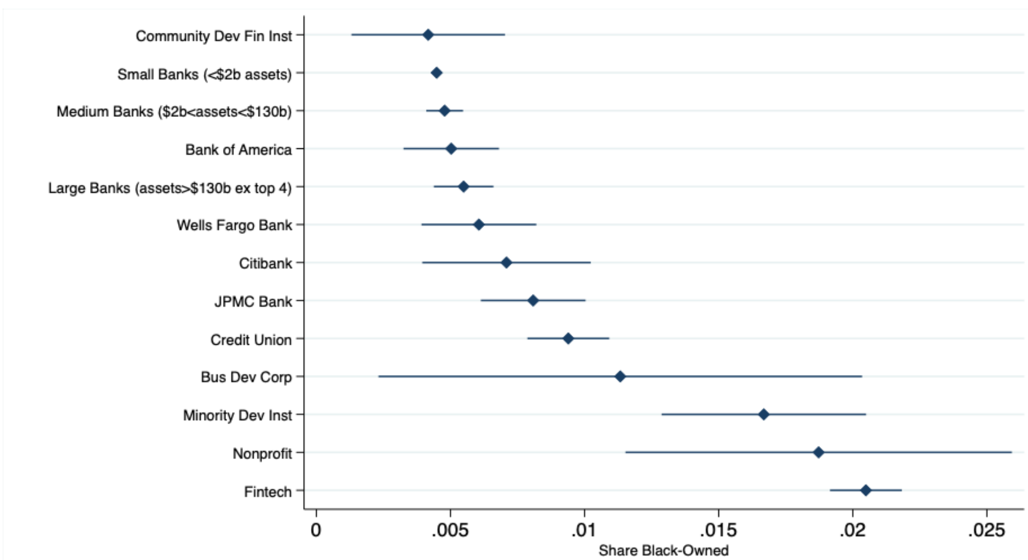
Appendix

Figure A.1: **Black-Owned Business PPP Lending by Institution Type (No Location Used in Race Prediction)**

A: No Controls



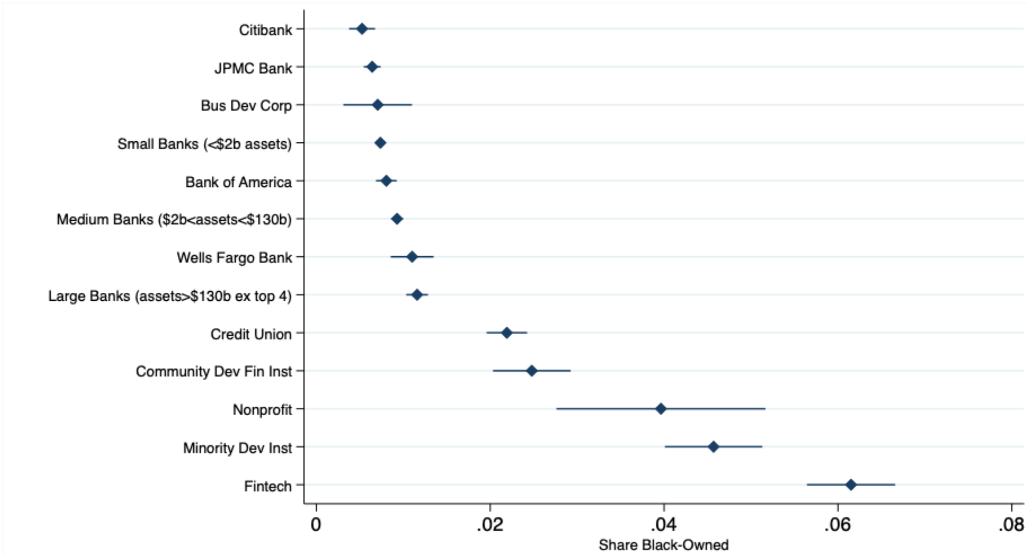
B: Full Controls



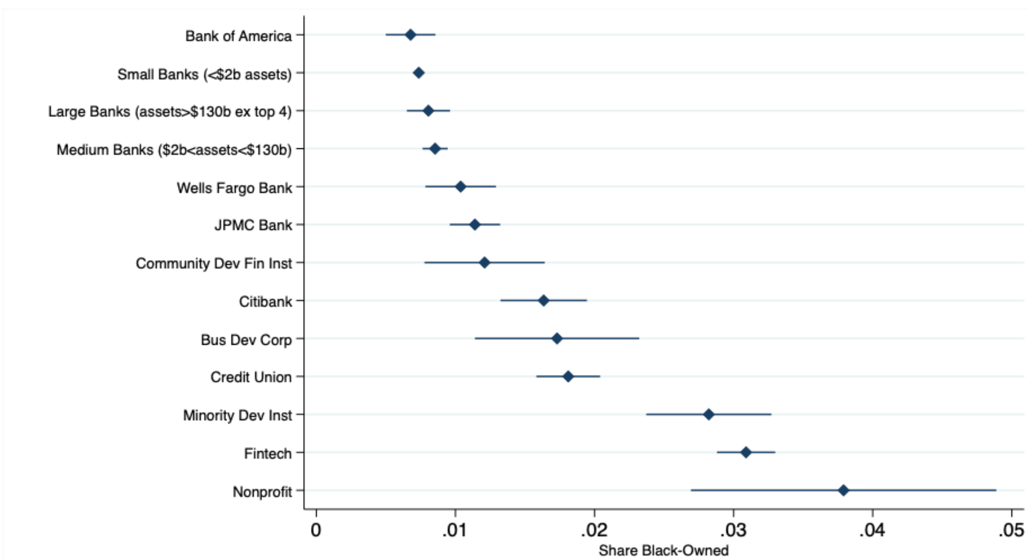
Note: This figure shows shares of PPP loans made to businesses predicted to be Black-owned by lender type. We classify businesses as Black-owned if our algorithm predicts a probability of Black ownership of over 50% based on the name and gender of the business owner only. Included in the sample are loans to self-employed individuals and sole proprietorships for which we observe business owner name in the data. Each graph presents coefficients from a regression of equation 1, where we add back the mean of the dependent variable among the excluded lender category. The dependent variable is an indicator for whether the business is Black-owned, and the independent variables are indicators for mutually exclusive categories for PPP lender type with small banks as the base category. The bottom graph includes fixed effects for borrower city, state, and NAICS3 industry, and loam amount percentiles. Standard errors are clustered by zip code.

Figure A.2: **Black-Owned Business PPP Lending by Institution Type (Alternative Predictive Cutoff)**

A: No Controls



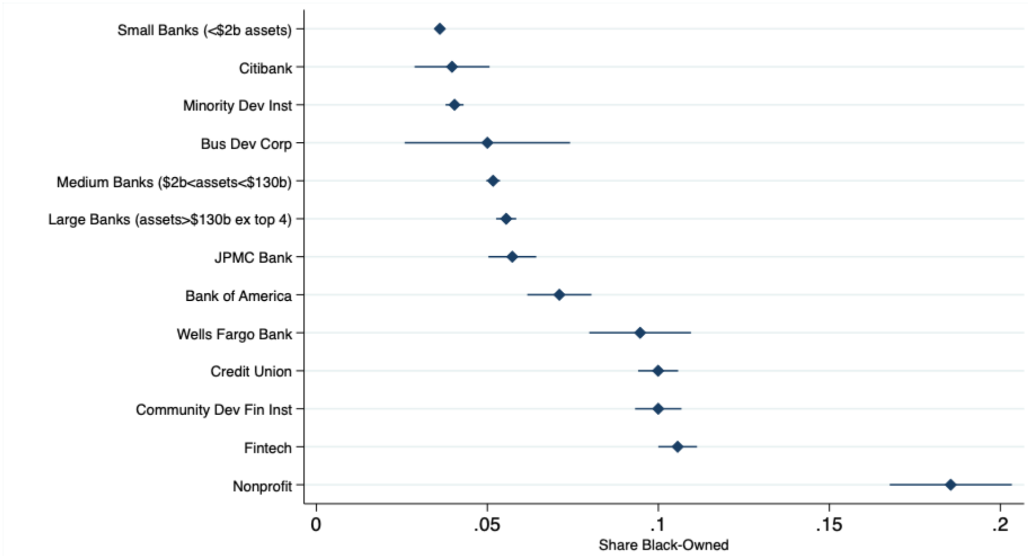
B: Full Controls



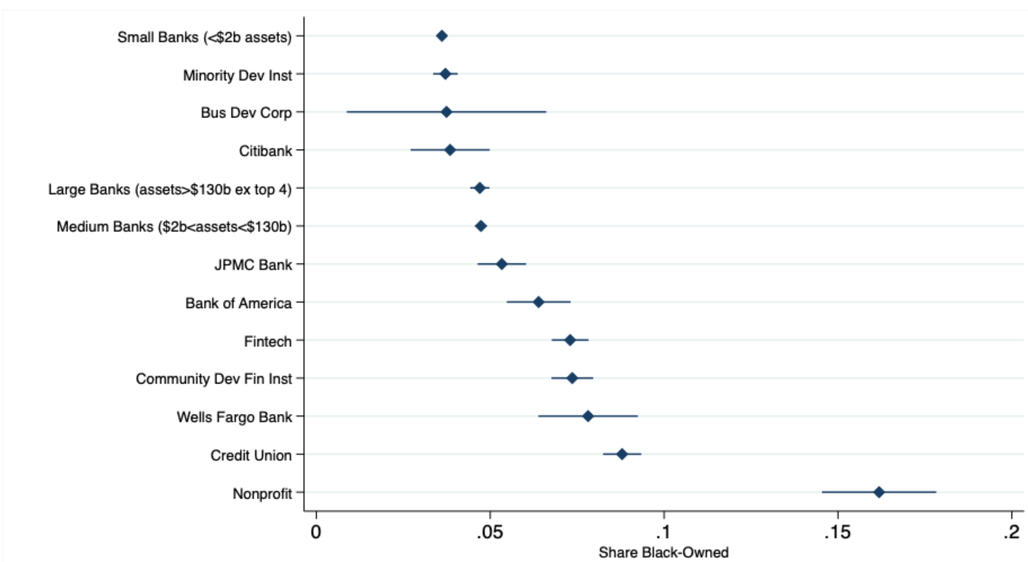
Note: This figure shows shares of PPP loans made to businesses predicted to be Black-owned by lender type. We classify businesses as Black-owned if our algorithm predicts a probability of Black ownership of over 75% based on the name and gender of the business owner and the business location. Included in the sample are loans to self-employed individuals and sole proprietorships for which we observe business owner name in the data. Each graph presents coefficients from a regression of equation 1, where we add back the mean of the dependent variable among the excluded lender category. The dependent variable is an indicator for whether the business is Black-owned, and the independent variables are indicators for mutually exclusive categories for PPP lender type with small banks as the base category. The bottom graph includes fixed effects for borrower city, state, and NAICS3 industry, and loam amount percentiles. Standard errors are clustered by zip code.

Figure A.3: **Black-Owned Business PPP Lending by Institution Type (Self-Identified)**

A: No Controls



B: Full Controls



Note: This figure shows shares of PPP loans made to businesses that self-identify as Black-owned by lender type. Included in the sample are loans to business for which self-identified race is included in the data. Each graph presents coefficients from a regression of equation 1, where we add back the mean of the dependent variable among the excluded lender category. The dependent variable is an indicator for whether the business is Black-owned, and the independent variables are indicators for mutually exclusive categories for PPP lender type with small banks as the base category. The bottom graph includes fixed effects for borrower city, state, and NAICS3 industry, and loam amount percentiles. Standard errors are clustered by zip code.