Federal Reserve Bank of Cleveland Working Paper Series

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Working Paper No. 22-18

June 2022

Suggested citation: Schweitzer, Mark E., and Brett R. Barkley. 2022. "Credit Availability for Minority Business Owners in an Evolving Credit Environment: Before and During the COVID-19 Pandemic." Working Paper No. 22-18. Federal Reserve Bank of Cleveland. https://doi.org/10.26509/frbc-wp-202218.

Federal Reserve Bank of Cleveland Working Paper Series
ISSN: 2573-7953

Credit Availability for Minority Business Owners in an Evolving Credit Environment: Before and During the COVID-19 Pandemic

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June 1, 2022

We apply data from the Federal Reserve's Small Business Credit Survey from 2016 to 2020 to estimate disparities in access to small business financing through loan denials and discouragement. We find that substantial credit disparities continue to exist despite the growth of fintech lenders, which prior research shows have expanded the set of small businesses receiving credit. Because the pandemic period brought many direct changes to the business and lending environment, we separately analyze the change to lending in 2020. PPP loans represented an unprecedented support for small businesses, support that was not dependent on the creditworthiness of businesses, but minority-owned businesses are estimated to have received a smaller fraction of the funds they applied for from the program.

JEL Codes: G21, L5, R3
Keywords: Small business lending, credit access, fintech

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1. Introduction and Literature Review

Wealth disparities between white and minority communities have largely persisted for decades after the Community Reinvestment Act (CRA) established that "banks have a continuing and affirmative obligation to help meet the credit needs of their local communities, including low- and moderate-income (LMI) neighborhoods where they are chartered. . ." (Federal Reserve System, 2018). While there are many underlying issues that have maintained the wealth gap, financing for business investments has been and continues to be a significant concern for minority businesses that frequently operate in LMI neighborhoods. Examining whether progress has been made on lending to minority communities should be an ongoing effort.

Prior research has focused on the elevated business loan denial rates evident in the Federal Reserve Board of Governors' Survey of Small Business Finances (SSBF). Cavalluzzo and Cavalluzzo (1998) and Blanchflower, Levine, and Zimmerman (2003) use data from the early surveys to conclude that significant racial/ethnic disparities in lending denial are evident. Bostic and Lampani (1999) show that even after controlling for neighborhood effects there is still a large and statistically significant Black-white difference in approval rates. Blanchard, Zhao, and Yinger (2005) and Asiedu, Freeman, and Nti-Addae (2012) apply enhanced estimation methods to the 1998 and 2003 SSBF to confirm the substantially larger denial rates for Black- and Hispanic-owned businesses. While the studies are generally in agreement and do not show a trend toward lower loan denials, 2003 was the last year the Federal Reserve conducted the SSBF.

More recent research has had to rely on data sources that have less detailed information on the businesses and more complicated sample frames than the SSBF. Bates and Robb (2015a, b), using the Kauffman Firm Survey results from 2008 to 2011, find that minority business owners are more likely to be discouraged from borrowing and more likely to always be rejected for credit. Because these papers analyze survey responses from businesses started in 2004 and still operating in 2008 to 2011, they build in a substantial survivor bias and the sample size is under 1000 for model results on credit decisions. Nonetheless, Bates and Robb do provide interesting evidence that the Community Reinvestment Act may be altering lending outcomes in minority neighborhoods by showing that neighborhood variables are insignificant when minority status is controlled for, although it would be good to see whether this is confirmed in a larger sample. Robb, de Zeeuw, and Barkley (2018) analyze the Federal Reserve System's 2016 Small Business Credit Survey (SBCS), which is a convenience sample weighted to match representative data from Census-managed surveys. They continue to find disparities in credit approval based on the race or ethnicity of the business owner and that Black business owners are more likely to report discouragement in credit access when compared to similar white-owned firms. They also note that a higher rate of Black- and Hispanic-owned firms apply for credit with nonbank online lenders but are unable to say how either lending disparities or the entry of new lenders has evolved. Without the specific controls included in the academic papers, the Federal Reserve's SBCS (Federal Reserve System, 2021a) continues to reveal important differences based on race and ethnicity in financing outcomes for small businesses.

The emergence of a new lender type (fintech firms: online non-bank lenders) could improve the availability of small business credit. Jagtiani and Lemieux (2017) document the rise of fintech lenders focused on small businesses and document that Lending Club loans tend to go to areas where bank branches are less present. They also show that Lending Club credit ratings are distinct from traditional risk scores, a distinction that might expand access to credit for businesses that are underserved by banks. The comparisons to bank credit are informative, but an analysis of potential racial disparities is not feasible because Jagtiani and Lemieux (2017) only observe approved loans without a comparable set of borrower characteristics for bank customers or businesses that are denied credit. Barkley and Schweitzer (2021) show that younger firms with fewer employees and less revenue are more likely to take a loan from an online lender in the 2016-2018 SBCS data. They apply treatment effects to show that fintech lenders reach a broader range of businesses than banks: 44 percent of fintech borrowers would have been unlikely to receive bank credit. Barkley and Schweitzer (2021) use race and ethnicity controls but do not directly examine lending discrepancies by race or ethnicity. Howell, et al. (2021) found that businesses that are likely to be minority-owned were significantly more likely to have received a PPP loan from a fintech lender rather than a bank. These results are particularly strong for businesses identified as Black-owned.

This paper applies data from the Federal Reserve's SBCS from 2016 to 2020 to estimate disparities in access to small business financing through loan denials and discouragement. We apply metrics from the literature on lending bias to the pre-pandemic data set to examine the evolution of credit access over time and the growth of fintech loans. We then analyze the extent to which fintech firms, in their apparent expansion of the small business credit market, have enabled minority business owners to more easily obtain credit. Because the pandemic period brought so many direct changes to the business and lending environment, we separately analyze the change to lending in 2020.

2. Small Business Credit Survey Data

The SBCS has five years of national data on the experiences of business owners from 2016 to 2020. Federal Reserve Banks and partner organizations contact businesses and asks them to complete a 15-minute online survey. Businesses are contacted through email addresses collected from a diverse set of organizations that serve small businesses. The sample covers businesses that received credit from a variety of sources, along with those that did not apply for credit. Respondents are asked about loan applications made over the prior year, business performance, and business characteristics. SBCS data are weighted to align with the distribution of the small firm (1 to 499 employees) population in the United States by number of employees, age, industry, geographic location (census division and urban or rural location), gender of owner(s), and race or ethnicity of owner(s), as reported by the Census Bureau and other official sources. See the 2021 SBCS Report on Employer Firms appendix for more detailed information on the survey methodology (Federal Reserve System, 2021b).

The SBCS also includes a reasonably complete set of owners' demographic characteristics, with 91 percent of businesses providing the race and ethnicity of the owner. To avoid the loss of data given weighting by the race and ethnicity of owners, the responses without race and ethnicity are imputed using a logistic model based on other firm characteristics and the demographic characteristics of the businesses' zip codes.

In Table 1, we separate survey responses by race/ethnicity and credit outcomes for the pre-pandemic period (2016-2019) and 2020. This table shows the raw difference in

the key outcomes that are examined in this paper. Outcomes for Black-owned businesses stand out: they have the highest application rate and the lowest rate of financing received. In addition, the pandemic period is clearly distinct in each of the outcomes for each racial/ethnic group. The combination of the pandemic's effects on businesses and the existence of emergency government programs like the Paycheck Protection Program (PPP) clearly altered outcomes in ways that limit the comparability of 2020 data: applications and approvals for regular financing (i.e., not PPP loans) dropped across all groups.
The small businesses, from just one employee up to 499 employees, that we include in this analysis are highly varied in ways that interact with their need for and access to credit. Table 2 shows some of the variables available in the SBCS from 2016-2019 that Barkley and Schweitzer show are relevant to the credit decision. As can be seen, these characteristics vary between racial and ethnic groups—differences that will underpin part of the credit outcomes—so it is critical to systematically evaluate their role and whether any disparities persist across race and ethnicity after accounting for them.

In addition, the 2020 survey includes a variety of questions about how businesses have responded to the COVID-19 pandemic. We will return to these variables in the discussion of credit availability in 2020.

3. Evaluating Hypotheses on Racial and Spatial Patterns of Credit

The information collected by the SBCS allows us to examine several critical hypotheses on racial and spatial access to credit with respect to the CRA's goal to ensure that banks meet the credit needs of their entire community consistent with safe and sound banking practices. Though CRA is technically race-neutral legislation, its enactment in

1977 is commonly understood as a response to the discriminatory practice of "redlining."[1] Our analysis, therefore, will assess lending disparities for low- and moderate-income (LMI) communities more generally (i.e., the language used by the CRA).

The primary research on lending disparities by race has used various years of the Federal Reserve's SSBF, but this survey was last conducted in 2003. Existing research (see the literature review) has highlighted racial discrepancies in lending for Black and Hispanic borrowers, after having controlled for business and credit variables that form an objective, unbiased model of the credit risk of the borrower. In this paper, we consider the denial of credit as a logistic function of a broad set of objective credit variables (C_i) and a set of demographic dummy variables R_i:

$$\Pr(D_i = 1) = \phi(\alpha_c C_i + \beta R_i) \tag{1}$$

The coefficients for β measure average discrepancies remaining in credit decisions after controls (C_i) by demographic group. If the model of credit risk were complete and accurate at the lender level, then any residual differences that were statistically significant between racial groups would be a measure of discrimination. We do not view our credit information as complete and expect that lenders apply distinct lending models to small-business credit; so any measured discrepancies shown by our model cannot necessarily be interpreted as a measure of lender discrimination. Relevant variables that are likely available to the lender but are not captured by the SBCS include the expected revenue of a given expansion or details of the asset holdings of the business or prior experiences with the borrower. However, the estimated lending discrepancies should still be viewed as

[1] "Redlining" was first used by the government-sponsored Home Owners' Loan Corporation (HOLC) and the Federal Housing Administration (FHA), which typically rated loans made in predominantly Black neighborhoods as high risk (color-coded red on original HOLC maps produced for cities throughout the United States). It eventually became a standard practice across the entire mortgage industry. For more information, see Adams (2009).

evidence consistent with discrimination in lending that should encourage regulators to more carefully examine lenders to ensure that equal access to credit is evident in their lending programs.

The set of borrowers that apply for credit is also likely to vary by race/ethnicity. Prior research has highlighted a tendency for Black and Hispanic borrowers to more frequently report that they did not seek credit because they did not think they would be approved. In attempting to identify such dynamics, it is important to account for characteristics such as a firm's financial performance, the owner's credit history, or the soundness of a business plan; otherwise, raw differences might just reflect that business owners are correctly interpreting their own objective credit information. We examine the extent to which discouragement differs by demographic group in the 2016-2019 SBCS data after introducing objective credit controls. Discouragement is estimated as a separate model with the same credit variables as in equation 1. The coefficients on the credit variables (α_c) can be interpreted as the expectations of typical small businesses, while β would represent an average level of group discouragement.

Both of the described hypotheses can also be examined over time in the SBCS. We might expect that racial and ethnic disparities would decline (or increase) as the market for bank credit has consolidated to fewer banks, with large banks now playing a more prominent role in small business credit markets than they used to and the credit application process becoming less dependent on personal, professional, or community networks. At the same time, a substantial entry of new (nonbank) fintech firms—which specialize in loans at much lower amounts than are typically offered by banks—might also alleviate disparities. Because the SBCS data collection process could introduce year-to-year sample variation, controlling for the risk of borrowers is particularly important when examining credit outcomes over time. In this case, we introduce an interaction of year in the survey with the demographic controls of interest to maintain a consistent risk-scoring environment across the sample period.

4. Geographic Disparities in Lending

The academic literature has focused on lending disparities by the race, ethnicity, or sex of the business owner, but a key component of the current fair lending policy regime, the Community Reinvestment Act (CRA), focuses on income-based geographic patterns of lending. The CRA sorts communities at the census-tract level according to whether their income level is low (less than 50 percent of reference median), moderate (50 to 80 percent), middle (80 to 120 percent) and upper (at least 120 percent of the reference median). The reference median is typically the median for the Metropolitan Statistical Area (MSA). However, for certain larger MSAs the median for a smaller division of the MSA is used, and for rural areas and micropolitan areas, the state median excluding MSAs is used as the reference median. These geographic distinctions are correlated with residential patterns of race/ethnicity and potentially for business ownership.

The SBCS does not have information on the specific census tract in which a business is located, but it does include a zip code, which we use to construct relative income levels, metropolitan area status, and race/ethnicity population shares by zip code. Zip codes can cross MSA and other boundaries, so we assign zip codes to MSAs according to the MSA accounting for the largest share of business addresses in a given zip code. Demographic and income information is taken from the American Community Survey. While the SBCS does not allow an analysis at the census-tract level (the geographic unit of analysis for CRA evaluations), zip-code-level characteristics are correlated with overlapping census tracts—but demographic differences across zip codes do tend to be less pronounced than differences observed across census tracts

Table 3 shows models of credit denial and borrower discouragement that are estimated primarily using geographic information. In all models, indicators for being located in a low-, moderate-, middle-, or high-income zip code within an MSA are included.[2] Because the SBCS sample includes fewer businesses in rural or micropolitan areas, in these areas we group low- and moderate-income zip codes together and middle- and high-income zip codes together. All models include census division and time fixed effects. To further control for areas potentially harder hit or less hit by cyclical economic conditions, we also include the change in the unemployment rate at the state level.

The first and fourth columns show estimates of credit denial and discouragement for CRA-related geographies and changes in unemployment rates. There are some potential geographic patterns here, but the only statistically significant patterns are for lower denial and discouragement rates in middle- and high-income rural areas. Adding information on the racial and ethnic composition of the zip codes (columns 2 and 5) does little to augment models of credit denial but does highlight some evidence that business owners in areas with larger Asian and Hispanic populations are significantly more likely on average to be discouraged borrowers. Businesses in zip codes with larger Black populations are more likely to be denied credit and to be discouraged, but neither of these results rise to

[2] The Census Bureau does not always report median incomes and populations for some zip codes. These are generally zip codes that are business only. We include these zip codes with high-income zip codes because the businesses that locate in these areas are likely to be more established entities.

standard levels of statistical significance. Overall, using population concentrations shows patterns but is not nearly as informative as using the race or ethnicity of the borrower. Columns 3 and 6 show results when the business owners' race/ethnicity are directly incorporated. These results show statistically significant, higher rates of loan denial for Black-, Native American-, and Hispanic-owned businesses and higher levels of discouragement for Black-, Asian-, and Hispanic-owned businesses. These results do not incorporate controls for other business characteristics that are likely to be relevant to credit decisions, but they do demonstrate the importance of directly accounting for the race of the business owner rather than relying on zip-code-level geographic proxies.

5. Lending Disparities and Discouragement

As the literature review indicated, lending disparities have been found by most prior work. The value of our analysis is the more recent period and the ability to apply a range of business characteristics as credit controls. The opportunity to examine these results in a potentially more competitive lending environment with the recent entry of fintech firms into small business lending is also unique to the literature. In our analyses, denials indicate that a business that sought credit during the year was not approved for any part of the desired credit. Discouragement is indicated when the business wanted credit but did not apply because the owner(s) believed that he or she would not qualify for credit.

The SBCS gives us several objective credit controls to implement. In all models, we include employment size, squared employment size, and indicator variables for each firm: age broken into four categories (0-2, 3-5, 6-10, 11-15, 16-20, and over 20); revenue ($100,000 to $1,000,000, $1 million to $10 million, and greater than $10 million); whether the firm is profitable; and whether revenue increased in the last 12 months. These variables are important characteristics in understanding the credit risk of a firm, and many of them are statistically significant in most models. In addition, we include the geographic controls from the basic CRA models discussed above, including the year-over-year change in the state unemployment rate. These variables have a limited impact on the model coefficients but some are statistically significant in select models. In models where the sample spans multiple years, we include dummy variables for year, though it turns out that these are not typically statistically significant. In general, the variables described are similar to those used in Barkley and Schweitzer (2021) that were shown to be reliable indicators for credit approval at banks or credit unions. That said, while appropriate credit control variables are important in this analysis, their coefficients are not our primary focus; so only a selection of credit variables are shown in the tables.

This analysis focuses on whether Black-, Hispanic-, Native American-, or Asian-owned firms have different credit experiences than white-owned firms once the objective credit variables are included in the regression.[3] Figure 1 reports average marginal effects for each group's likelihood of being denied financing (top pane) and being discouraged (bottom pane) relative to white-owned firms. More specifically, a bar's position in the figure relative to the zero line indicates the likelihood of credit denial compared with similar white-owned firms. In each case, marginal effects are reported for models including the baseline variables discussed above and separately for models also including the firm's self-reported credit score. In the base model (Figure 1), the marginal effect for Black-owned businesses is 0.072, implying that a Black-owned business is 7.2 percentage

[3] Credit difference for veteran- and women-owned businesses is not the focus of this analysis, but indicator variables for these groups are included in the results to avoid any correlated effects.

points more likely than an equivalent white-owned firm to be denied financing, which is statistically significant at even the 99 percent confidence level (indicated by the width of the bar: wide for 90 percent, mid-width for 95 percent and narrow for 99 percent confidence). Hispanic-owned firms experience a smaller difference in denials and one that is only statistically significant at the 90 percent confidence level.

One key variable that we excluded from the base model is the business owner's credit score. While credit scores are widely used in lending decisions, Henderson, et al. (2015) criticize credit scores as still differing on average by race after objective business factors have been accounted for. Their work was based on analysis of a set of startups drawn from the Kaufman panel that should be well-described by the information included in the SBCS and relatively comparable. They find significant racial differences in credit scores despite credit scoring companies being legally prohibited from including race and ethnicity in their models. This indicates that other factors included in widely applied credit scoring models may act as proxies for race and ethnicity.

In the SBCS, respondents are asked to report either the business's credit score or the owner's personal credit score. From these scores, we create one variable that indicates that a firm has low, middle, or high credit risk. Not all businesses report a credit score; so we also include a variable level indicating whether the business did not report a score. Adding this credit score variable to the model tends to lower the magnitude and statistical significance of the results. For Black-owned businesses the discrepancy falls to 4.4 percentage points and is now statistically significant with 95 percent confidence. The Hispanic figure drops to 2.8 percentage points and is no longer statistically significant at conventional levels. These shifts should not be surprising, as other credit controls reduced the measured race and ethnicity effects, but as shown by Henderson, et al. (2015) credit scores may build in racial and ethnic biases. Asian-, women-, and veteran-owned businesses show no statistically significant discrepancies in denials at conventional levels in either model. These results largely confirm the primary results of prior research.

One potential problem for denial models is that the sample may be distorted by the decision to apply for credit. Ideally, all racial and ethnic groups would be just as likely to apply for credit given the same underlying business and credit fundamentals. The bottom pane of Figure 1 reports results for models estimated on an indicator of being discouraged from applying for credit: businesses that self-selected out of credit. These results are similar to denials with a range of business characteristics influencing the decision to apply for credit. The primary difference is that relative to credit denial models, the effects of race and ethnicity generally are larger and now statistically significant for Asian-owned businesses. They continue to be statistically significant for Black-owned businesses in both models and for Hispanic-owned businesses when credit scores are not included. While the literature has focused on denial rates, these differences in discouragement are large enough to have substantial implications for credit for minority businesses.

Adding in credit scores to the model of borrower discouragement shifts the estimates for Black- and Hispanic-owned businesses substantially lower. Black-owned businesses are measured to be just 5 percentage points more likely to be discouraged from applying once credit scores are included, which is still highly statistically significant. The large role played by credit scores may indicate that the business owner's knowledge of his or her own credit score represents a substantial barrier to credit applications for these groups. Interestingly, introducing credit scores does little to alter estimated differences for Asian-owned businesses, suggesting that credit reports bring little additional information for this demographic group.

These results show that differences found in past research are still evident in the 2016-2019 data. We now turn to analyzing whether the entry of fintech firms has mattered and how results are different during the pandemic.

6. Has the Entry of Fintech Lenders Increased Access to Credit?

As a starting point in assessing whether the entry of new lenders has limited credit disparities, we apply an interaction of SBCS survey year with the Black and Hispanic dummy variables to evaluate the extent to which denials change over time. The standard errors on model coefficients—and in turn, the marginal effects—are generally large enough to make comparisons from year to year statistically insignificant. Figure 2 (top pane) reports the marginal effects for denial rates over the sample period for Black- and Hispanic-owned businesses. It shows that, except for 2017, lending disparities within a single year are often statistically insignificant, even at lower levels of confidence. The pattern in the coefficients is also not generally increasing or decreasing over time. The results for discouragement are similar in that there is no discernible trend over time, but the effects tend to be larger than the estimates in the denial models and more often statistically significant, at least for Black-owned firms. Our interpretation of these results is that the SBCS sample is not large enough to determine annual levels of racial disparities in denials with precision. Nonetheless, the 2016-2019 period still points to substantial, statistically significant differences.

The lack of a clear trend in denials for Black- and Hispanic-owned businesses is not encouraging evidence of improved borrower conditions given a substantial rise in the use of fintech lenders. Nonetheless, it could be the case that fintech firms have increased credit to minorities but not by enough to overcome the inherent variation in the SBCS or that these effects have been offset by changes in the terms offered by traditional lenders.

In addition to the year-by-year results reported in Figure 2, we also used lender-type interactions in the logit model to more directly account for how fintech firms' lending decisions may have differed from those of banks and credit unions. Barkley and Schweitzer (2021) document that fintech lenders offer credit to riskier borrowers that banks are less likely to serve, but that model is complicated when further disaggregation of the credit decisions is considered.

Instead, we apply an extension of the simple model shown in equation 1 to allow for differences in lending decision by lender type. Borrowers can pursue credit through multiple lenders and the SBCS records the lender type for up to five credit applications in the last 12 months. The SBCS does not report the outcome of each decision but does report the fraction of "financing dollars that your business sought in the last 12 months" that were received. When the fraction received is zero, we treat that as credit denial, which is the outcome reported in Figure 3. Businesses that report having applied for credit through an online lender (fintech) or a nonbank finance company are identified in indicator variables I^F and I^N. These indicator variables are used to augment equation 1 to account for lending channel differences:

$$\Pr(D_i = 1) = \phi(\alpha_c C_i + \gamma^F I_i^F + \gamma^N I_i^N + \beta R_i + \gamma^{FR} R_i I_i^F + \gamma^{NR} R_i I_i^N) \qquad (2)$$

These specifications allow the probability of denial to respond directly to the increased access to fintech and nonbank finance companies while maintaining the controls for riskier borrowers implemented by the dominant lending channel, banks. If applying to either fintech or nonbank finance companies makes credit more available to borrowers on average, then γ^F or γ^N should be less than zero. A statistically significant negative γ^F would parallel the results of Barkley and Schweitzer (2021). The addition of interactions with race/ethnicity indicators (γ^{FR} or γ^{NR}) allows for these lending channels to either further advantage or disadvantage borrowers from the identified racial/ethnic groups. If, for example, fintech lenders were just as likely to provide credit given credit-relevant business characteristics but with no difference by the race of the business owner, then $\gamma^{FR} = -\beta$ for all racial and ethnic groups. Of course, incompleteness of the credit model and the inability to distinguish between specific applications are likely to introduce additional variability in these results.

Our estimates from this model support the narrative that the denial rates of online lenders are generally lower. Expressed as an average marginal effect, having applied with an online lender lowers the probability of denial by 11.6 percentage points on average regardless of race/ethnicity. Figure 3 shows the marginal effect on the probability of credit denial relative to white-owned businesses, separated by lender type. Denial rates continue to be higher for Black-owned businesses in the model without credit scores, regardless of whether the businesses applied with a fintech firm. For the base model, both Black differentials are statistically significant at the 95 percent confidence level—but importantly, while the online lender effect is lower, the two estimates are not statistically different from each other. Neither Hispanic- nor Asian-owned businesses show a statistically significant denial rate for either lender type compared to white-owned businesses. As with prior estimates, including credit scores lowers the point estimates, and the estimated differences in denial rates are now not significant for any of the racial and ethnic categories. Overall, while online lenders have expanded credit availability, they do not appear to have disrupted the racial and ethnic differences in credit access at this point.

7. How Did Access to Credit Change During the Pandemic?

The pandemic altered both the demand for and the supply of credit. On the supply side, several fintech firms announced that they had halted lending while banks reduced business lending and expanded their allowances for bad loans. Businesses reported sharp reductions in business activity levels in the SBCS, applied less frequently for traditional credit, and relied more on PPP loans (Federal Reserve Banks, 2021a). In order to make the periods as comparable as possible, we apply the model developed in Section 4 to the 2020 SBCS data.

Figure 4 repeats the analyses shown in Figure 1 on 2020 data for conventional credit applications (i.e., not including PPP credit applications). We separately estimate results for PPP loans and exclude other government-aided credit from these results. There were fewer conventional credit applications reported in 2020 (down 5 percentage points overall and up 10 percentage points among Hispanic- and Native American-owned businesses), and many of these were in the early part of 2020 (Table 1). As was evident in Figure 2, confidence intervals are wider when applied to a single year's data. The point estimates of the marginal effects in the credit denial models are not very different from what was seen in the pre-pandemic models, but only the base model estimate for Black-owned businesses is statistically significant at conventional levels (95 percent).

The reduced number of credit applications suggests that we focus more on discouragement. Interestingly, slightly fewer businesses overall reported being discouraged in 2020 than during the 2016-2019 period (Table 1), but we are examining the discouragement of minority-owned businesses relative to that experienced by white-owned businesses in 2020. The lower panels of Figure 4 show sharp differences in discouragement of minority-owned firms. The base model implies levels of discouragement that are 6.9 and 16.7 percentage point greater for Hispanic- and black-owned businesses, respectively, compared with similar white-owned businesses. All of these estimates are statistically significant with 99 percent confidence. Including credit scores again lowers the point estimates of discouragement for Black- and Hispanic-owned businesses, but the estimates are larger than comparable estimates using 2016-2019 data. Despite being drawn from just one year's data, these estimates are generally statistically significant at high levels.

The other unusual feature of the 2020 credit market was the introduction of the Paycheck Protection Program, which provided government-funded and forgivable loans under certain conditions. A key feature of the program was the lack of any credit risk estimates in the underwriting of these loans—they were intended to be a subsidy to support employment in small businesses despite the challenging circumstances that many small businesses faced. The amount available to businesses was largely determined by past payroll figures and widely communicated. The program was heavily utilized, with 76 percent of SBCS respondents applying for credit through the program.

Despite the broad applicability of the program, there were differences in the frequency of PPP loans per capita in low- and moderate-income communities and by businesses located in census tracts with larger minority populations (Schweitzer and Borawski 2021). Since the program ignored credit risk and was intended to operate as a subsidy, the vast majority of applicants for PPP loans reported receiving the full amount of the applied-for funds. Still, the 2021 SBCS Report on Employer Firms documented large differences across race/ethnicity in PPP application rates and the share receiving the full PPP amount applied for. We show similar numbers for PPP approval in Table 1, but this could reflect younger or otherwise less-prepared firms applying more often or being prone to over-estimating the amounts they qualified for. Our objective credit controls should control for these potential dynamics and provide a clearer picture of differences across race/ethnicity.

The upper panels of Figure 5 show the marginal effects of race/ethnicity for reporting less than the full amount received from their PPP loan application. The underlying model is the same used previously in this paper, but in this case, the controls for firm characteristics are supposed to pick up differences in the businesses that might have influenced their application rates or qualification under the program rules. There is a clear pattern that Black- and Hispanic-owned businesses were substantially more likely to report receiving only a partial amount of their PPP loan. There is little difference in the results if credit scores are included in the estimation. Even though credit scores were not used in decisions, credit scores might still signal financially fragile firms. For these two groups, the differences are large and statistically significant. In addition, the lower panel shows that Black- and Hispanic-owned businesses were more likely to report not applying for PPP loans for reasons consistent with discouragement in commercial lending, rather than the program not being needed or not qualifying for the program. So even in the PPP loan program, which was designed to reach firms regardless of credit risk, we find some notable differences by race and ethnicity.

8. Conclusions and Policy Recommendations

Using SBCS data from 2016-2020, we sought evidence that credit disparities seen in the earlier literature on small business lending might have waned over time with the rise of fintech lenders to small businesses. Instead, we found that substantial credit disparities continue to exist, even as fintech lenders have expanded the set of small businesses that receive credit relative to banks and credit unions. These results are particularly clear when credit scores are excluded from the model. Prior research (Henderson, et al. 2015) has argued that credit scores can incorporate racial biases even when factors associated with default have been incorporated. We don't have any new results to contribute to this discussion, but we think it is important to evaluate models both with and without credit scores to assess differences in credit access.

The pandemic weakened potential borrowers and lenders in general, but in our analysis, the challenges were greater for minority-owned businesses. The general pullback in loan applications puts the focus on discouragement figures, and statistically significant differences are seen for most categories of minority-owned businesses. Our model includes important controls for the age, size, and revenue of the businesses; so these disparities should be a policy concern. PPP loans in 2020 represented an unprecedented support for small businesses, support that was not dependent on the creditworthiness of businesses, but we continued to see that minority-owned businesses were more likely to receive less funding than they applied for from the program. They also were less likely to apply for PPP loans for reasons that we interpret as consistent with discouragement. The PPP loan program clearly reached a wide swath of small businesses, including low- and moderate-income communities (Schweitzer and Borawski, 2021), but our results from actual and potential borrowers show that the PPP loan program did leave out groups of minority-owned businesses in 2020.

Our results should inform ongoing policy discussions about access to credit and the implementation of the Community Reinvestment Act. We see evidence that the geographic focus areas of the CRA do not appear to be disadvantaged (at least when examined at the zip code level) but introducing information on the specific race and ethnicity of business owner continues to reveal differences in credit access. This implies that the broader issue of minority-owned businesses' access to credit is largely unsolved—especially with respect to Black business owners. Fintech lenders are a valuable substitute in market segments that have limited access to credit, but we find that their lending patterns do not shift lending to minority-owned businesses in a meaningful way. The combination of these results suggests that the credit needs of minority-owned small businesses might require more specialized interventions in national or local lending markets.

References

Adams, Stella J. 2009. "Putting Race Explicitly into the CRA." *Community Development Innovation Review*, February 2009. https://www.frbsf.org/community-development/publications/community-development-investment-review/2009/february/cra-community-reinvestment-act-race/.

Asiedu, Elizabeth, James A Freeman, and Akwasi Nti-Addae. 2012. "Access to Credit by Small Businesses: How Relevant Are Race, Ethnicity, and Gender?" *American Economic Review* 102 (3): 532–37. https://doi.org/10.1257/aer.102.3.532.

Barkley, Brett, and Mark E. Schweitzer. 2021. "The Rise of Fintech Lending to Small Businesses: Businesses' Perspectives on Borrowing." *International Journal of Central Banking* 17 (1): 35–65. https://ideas.repec.org/a/ijc/ijcjou/y2021q1a2.html.

Bates, Timothy, and Alicia Robb. 2013. "Greater Access to Capital Is Needed to Unleash the Local Economic Development Potential of Minority-Owned Businesses:" *Economic Development Quarterly*, February. https://doi.org/10.1177/0891242413477188.

———. 2015. "Has the Community Reinvestment Act Increased Loan Availability among Small Businesses Operating in Minority Neighbourhoods?" *Urban Studies* 52 (9): 1702–21. https://doi.org/10.1177/0042098014534903.

———. 2016. "Impacts of Owner Race and Geographic Context on Access to Small-Business Financing." *Economic Development Quarterly* 30 (2): 159–70. https://doi.org/10.1177/0891242415620484.

Blanchard, Lloyd, Bo Zhao, and John Yinger. 2005. "Do Credit Market Barriers Exist for Minority and Women Entrepreneurs?" Working Paper 74. Center for Policy Research, Maxwell School, Syracuse University. https://ideas.repec.org/p/max/cprwps/74.html.

Blanchflower, David G., Phillip B. Levine, and David J. Zimmerman. 2003. "Discrimination in the Small-Business Credit Market." *The Review of Economics and Statistics* 85 (4): 930–43. https://doi.org/10.1162/003465303772815835.

Board of Governors of the Federal Reserve System. 2018. "History of the CRA." December 7, 2018. https://www.federalreserve.gov/consumerscommunities/cra_history.htm.

Bostic, Raphael W., and K. Patrick Lampani. 1999. "Racial Differences in Patterns of Small Business Finance: The Importance of Local Geography." In *Business Access to Capital and Credit*, 149–79. Arlington, VA: Federal Reserve Bank of Chicago. https://www.fedinprint.org/item/fedhpr/38645.

Cavalluzzo, Ken S., and Linda C. Cavalluzzo. 1998. "Market Structure and Discrimination: The Case of Small Businesses." *Journal of Money, Credit and Banking* 30 (4): 771–92. https://doi.org/10.2307/2601128.

Federal Reserve Banks. 2021a. "Small Business Credit Survey: 2021 Report on Employer Firms." Small Business Credit Survey. https://doi.org/10.55350/sbcs-20210203.

———. 2021b. "Small Business Credit Survey: 2021 Report on Firms Owned by People of Color." Small Business Credit Survey. https://doi.org/10.55350/sbcs-20210415.

Henderson, Loren, Cedric Herring, Hayward Derrick Horton, and Melvin Thomas. 2015. "Credit Where Credit Is Due? Race, Gender, and Discrimination in the Credit Scores of Business Startups." *The Review of Black Political Economy* 42 (4): 459–79. https://doi.org/10.1007/s12114-015-9215-4.

Howell, Sabrina T., Theresa Kuchler, David Snitkof, Johannes Stroebel, and Jun Wong. 2021. "Automation and Racial Disparities in Small Business Lending: Evidence from the Paycheck Protection Program." Working paper 29364. National Bureau of Economic Research. https://doi.org/10.3386/w29364.

Jagtiani, Julapa A., and Catharine Lemieux. 2017. "Fintech Lending: Financial Inclusion, Risk Pricing, and Alternative Information." Working paper 17-17. Federal Reserve Bank of Philadelphia. https://ideas.repec.org/p/fip/fedpwp/17-17.html.

Robb, Alicia, Brett Barkley, and Mels de Zeeuw. 2018. "Mind the Gap: How Do Credit Market Experiences and Borrowing Patterns Differ for Minority-Owned Firms?" Discussion paper 2018-03. Federal Reserve Bank of Atlanta. https://doi.org/10.29338/dp2018-03.

Robb, Alicia M., and David T. Robinson. 2014. "The Capital Structure Decisions of New Firms." *The Review of Financial Studies* 27 (1): 153–79. https://doi.org/10.1093/rfs/hhs072.

Schweitzer, Mark E., and Garrett Borawski. 2021. "How Well Did PPP Loans Reach Low- and Moderate-Income Communities?" *Economic Commentary (Federal Reserve Bank of Cleveland)*, no. 2021-13 (May). https://doi.org/10.26509/frbc-ec-202113.

Table 1: Basic weighted sample characteristics, pre-pandemic vs. pandemic

	Race/ethnicity of ownership					
	White	Black	Asian	Native American	Hispanic	Total
Pre-pandemic (2016-2019)	%	%	%	%	%	%
Share that applied for financing, past 12 months						
No (n=16,865)	57.3	49.9	62.9	50.4	50.9	57.4
Yes (n=14,238)	42.7	50.1	37.1	49.6	49.1	42.6
Total (n=31,103)	100.0	100.0	100.0	100.0	100.0	100.0
Discouraged						
No (n=13,974)	87.2	65.5	81.0	82.1	75.4	85.5
Yes (n=2,187)	12.8	34.5	19.0	17.9	24.6	14.5
Total (n=16,161)	100.0	100.0	100.0	100.0	100.0	100.0
Financing received						
Denied (n=1,882)	17.0	34.8	20.4	29.4	27.6	18.4
Approved (n=8,934)	83.0	65.2	79.6	70.6	72.4	81.6
Total (n=10,816)	100.0	100.0	100.0	100.0	100.0	100.0
Online financing						
Denied (n=565)	20.3	38.1	25.2	34.4	31.6	22.3
Approved (n=1,820)	79.7	61.9	74.8	65.6	68.4	77.7
Total (n=2,385)	100.0	100.0	100.0	100.0	100.0	100.0
Traditional financing						
Denied (n=2,340)	29.4	62.2	35.9	42.9	48.9	31.9
Large bank approved (n=2,687)	28.8	16.9	37.8	19.2	28.2	29.4
Small bank approved (n=3,287)	37.4	16.8	23.3	30.8	17.9	34.4
Credit union approved (n=309)	4.4	4.1	3.0	7.1	5.1	4.3
Total (n=8,623)	100.0	100.0	100.0	100.0	100.0	100.0
Pandemic (2020)						
Share that applied for financing, past 12 months						
No (n=6,236)	62.7	54.5	64.5	60.1	61.3	62.7
Yes (n=4,059)	37.3	45.5	35.5	39.9	38.7	37.3
Total (n=10,295)	100.0	100.0	100.0	100.0	100.0	100.0
Discouraged						
No (n=5,259)	89.5	65.7	81.1	85.5	80.6	87.8
Yes (n=886)	10.5	34.3	18.9	14.5	19.4	12.2
Total (n=6,145)	100.0	100.0	100.0	100.0	100.0	100.0
Financing received						
Denied (n=694)	20.9	43.7	18.4	15.0	38.5	22.2
Approved (n=2,014)	79.1	56.3	81.6	85.0	61.5	77.8
Total (n=2,708)	100.0	100.0	100.0	100.0	100.0	100.0
Online financing						
Denied (n=200)	31.9	63.9	43.0	28.7	41.2	34.7
Approved (n=312)	68.1	36.1	57.0	71.3	58.8	65.3
Total (n=512)	100.0	100.0	100.0	100.0	100.0	100.0
Traditional financing						
Denied (n=644)	27.6	57.6	33.7	26.7	51.6	30.2
Large bank approved (n=601)	30.0	18.1	32.1	6.0	29.5	29.7
Small bank approved (n=622)	37.6	19.2	33.0	19.5	16.4	35.5
Credit union approved (n=81)	4.8	5.1	1.2	47.7	2.6	4.6
Total (n=1,948)	100.0	100.0	100.0	100.0	100.0	100.0
PPP approval						
Full amount approved (n=5,913)	79.4	42.6	68.1	63.6	60.9	76.7
Partial amount approved (n=2,159)	20.6	57.4	31.9	36.4	39.1	23.3
Total (n=8,072)	100.0	100.0	100.0	100.0	100.0	100.0
PPP Discouraged						
No (n=9,880)	97.1	84.1	93.7	84.7	91.1	96.1
Yes (n=517)	2.9	15.9	6.3	15.3	8.9	3.9
Total (n=10,397)	100.0	100.0	100.0	100.0	100.0	100.0

Note: For reporting race/ethnicity, only Non-Hispanic respondents are included in white, Black, Asian, and Native American groupings. We cannot report weighted sample characteristics with survey respondents who did not identify their race/ethnicity as race/ethnicity is one of the componentsthat the sample is weighted by.

Table 2: Select credit factors by race/ethnicity, survey years 2016-2019

	White	Black	Asian	Native American	Hispanic
Age					
0-2 years	18.9	29.5	25.4	23.6	28.2
3-5 years	12.8	16.1	15.9	16.0	15.8
6-10 years	19.2	23.4	23.7	19.8	24.1
11-15 years	13.8	13.2	13.8	15.4	13.3
16-20 years	9.6	9.6	9.2	12.9	7.5
21+ years	25.8	8.3	12.0	12.3	11.1
Employee size					
1-4 employees	53.8	66.7	53.2	59.6	64.2
5-9 employees	18.3	16.6	20.4	17.8	17.1
10-19 employees	12.9	9.6	13.6	10.1	9.6
20-49 employees	9.6	4.8	7.6	6.7	6.2
50-499 employees	5.4	2.3	5.2	5.7	2.9
Revenue					
<$100K	15.3	41.0	18.5	26.4	26.8
$100K-$1M	49.0	44.4	48.3	48.8	51.5
$1M-$10M	31.2	13.2	30.1	21.4	19.0
$10M+	4.5	1.4	3.0	3.4	2.7
Profitability					
At a loss	23.5	37.4	27.4	31.6	27.7
Broke even	18.9	20.7	18.4	23.1	20.1
At a profit	57.6	41.9	54.2	45.3	52.2
Credit score risk					
Low risk	49.7	32.4	51.7	41.6	39.9
Medium risk	14.5	29.9	17.2	23.4	25.8
High risk	3.1	15.7	4.1	9.7	8.8
Did not respond	32.7	22.0	27.1	25.3	25.5
Unemployment rate (yoy change)					
mean	-0.425	-0.460	-0.457	-0.373	-0.474
N	23383	2505	1163	334	1930

Note: Sample characteristics represent the percentage of survey respondents in each category, except for the unemployment rate variables, which represent the average change in the state unemployment rate for the state in which a firm is located during the time period noted.

Table 3: Pre-pandemic geographic models of credit: Denial and discouragement

	Denials			Discouraged		
	CRA Geo	+ Zip >30%	+ Race	CRA Geo	+Zip >30%	+ Race
Metro. Low Inc	0.278	0.107	0.173	-0.059	-0.203	-0.197
	(0.237)	(0.260)	(0.239)	(0.240)	(0.255)	(0.249)
Metro. Mod Inc.	-0.004	-0.103	-0.061	-0.104	-0.195	-0.179
	(0.123)	(0.136)	(0.124)	(0.116)	(0.125)	(0.118)
Metro. Middle Inc.	0.155	0.132	0.164	-0.101	-0.122	-0.099
	(0.100)	(0.101)	(0.100)	(0.087)	(0.088)	(0.088)
Micro. Low-Mod	-0.173	-0.214	-0.166	-0.673	-0.706	-0.592
	(0.575)	(0.564)	(0.579)	(0.649)	(0.656)	(0.648)
Micro. Mid-High	-0.232	-0.232	-0.192	-0.233	-0.222	-0.178
	(0.167)	(0.168)	(0.167)	(0.153)	(0.155)	(0.154)
Rural Low-Mod	-0.109	-0.152	-0.076	-0.340	-0.392	-0.346
	(0.567)	(0.540)	(0.570)	(0.519)	(0.523)	(0.536)
Rural Mid-High	-0.584***	-0.601***	-0.539**	-0.341*	-0.311	-0.258
	(0.209)	(0.211)	(0.210)	(0.191)	(0.192)	(0.192)
Change in Unem Rate	-0.070	-0.052	-0.068	-0.200*	-0.186*	-0.187*
	(0.114)	(0.114)	(0.114)	(0.108)	(0.109)	(0.109)
Hispanic Pop >30%		0.155			0.236**	
		(0.124)			(0.114)	
Black Pop >30%		0.232			0.134	
		(0.145)			(0.134)	
Asian Pop >30%		-0.102			0.389**	
		(0.254)			(0.189)	
Native Pop >30%		-0.142			0.529	
		(0.915)			(0.673)	
Black			0.903***			1.262***
			(0.111)			(0.099)
Asian			0.119			0.431***
			(0.173)			(0.134)
Native Amer.			0.749**			0.471
			(0.302)			(0.296)
Hispanic			0.548***			0.768***
			(0.143)			(0.116)
Observations	10507	10406	10507	15607	15441	15607
Pseudo R^2	0.012	0.013	0.018	0.007	0.009	0.019

Standard errors in parentheses
Results reported are for 2016-2019. Select variables shown. All models also include census division, YoY change in state unemployment rate, and year indicator variables.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

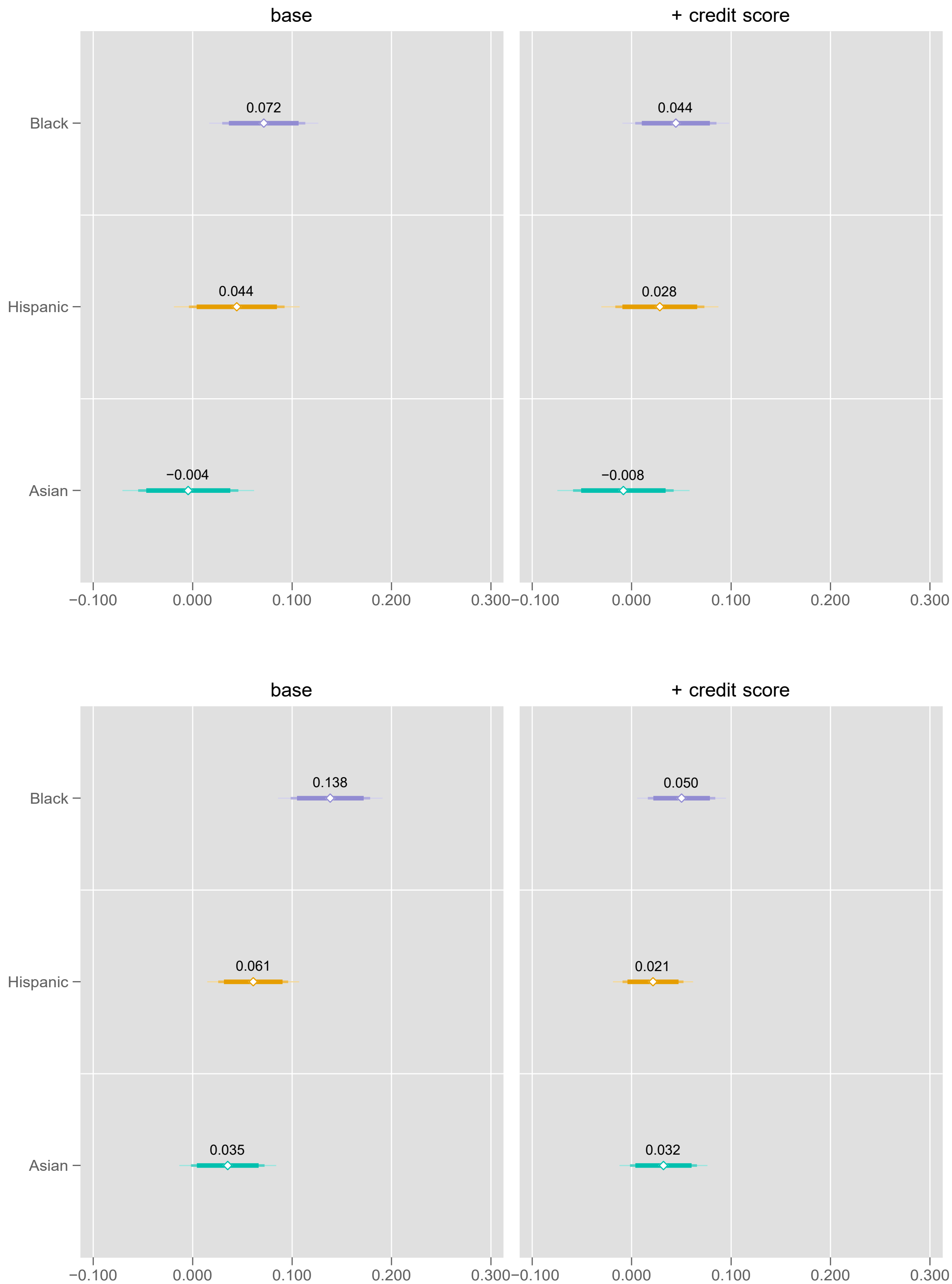


Figure 1: Predicted probabilities of (Top) being denied financing and (Bottom) being discouraged from applying relative to white-owned firms, 2016-2019. Probabilities are reported as average marginal effects. Source: Authors' calculations, Federal Reserve Banks, 2016-2020 Small Business Credit Survey.

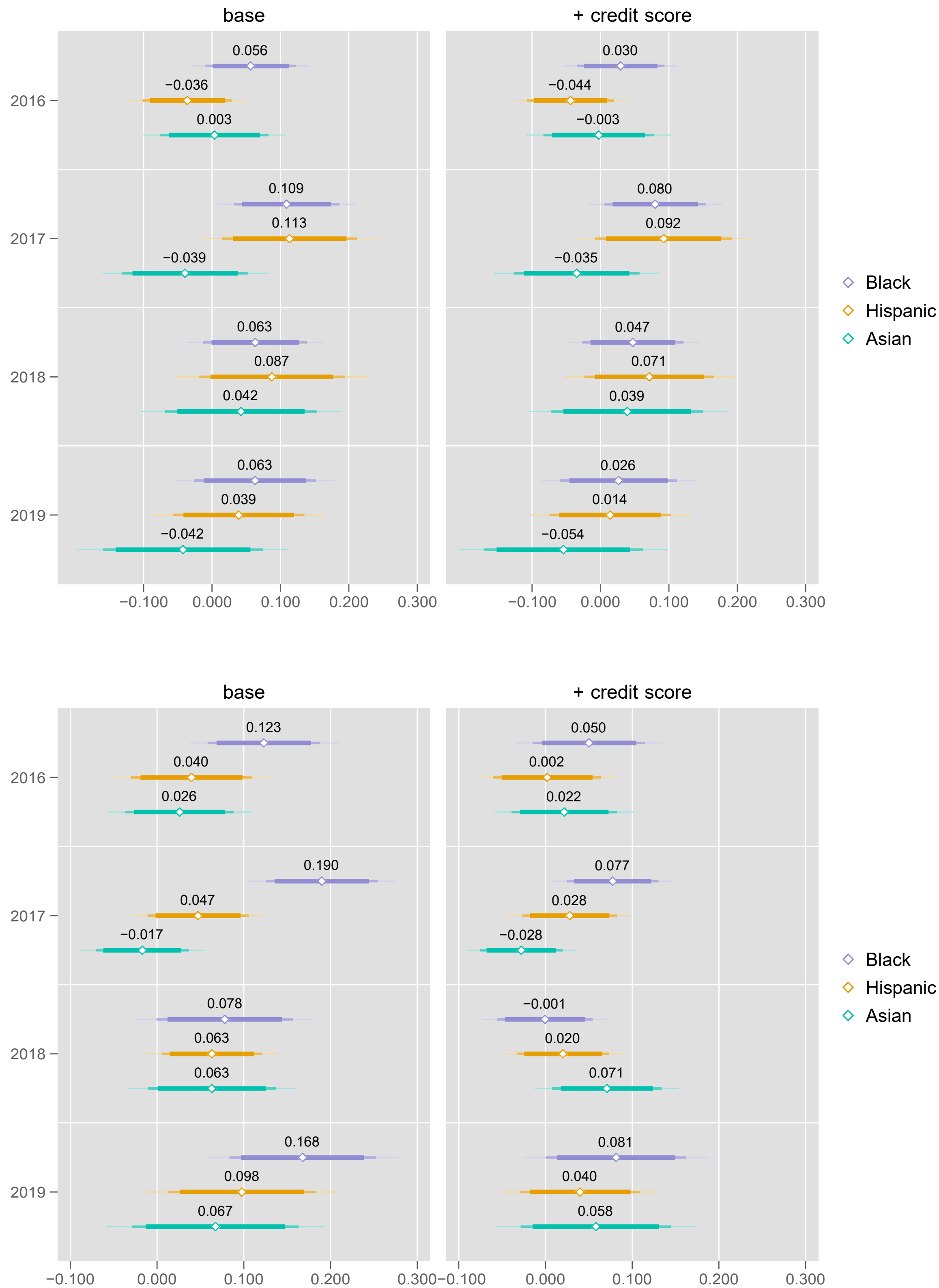


Figure 2: Predicted probabilities by year of (Top) being denied financing and (Bottom) being discouraged from applying relative to white-owned firms. Probabilities are reported as average marginal effects. Source: Authors' calculations, Federal Reserve Banks, 2016-2020 Small Business Credit Survey.

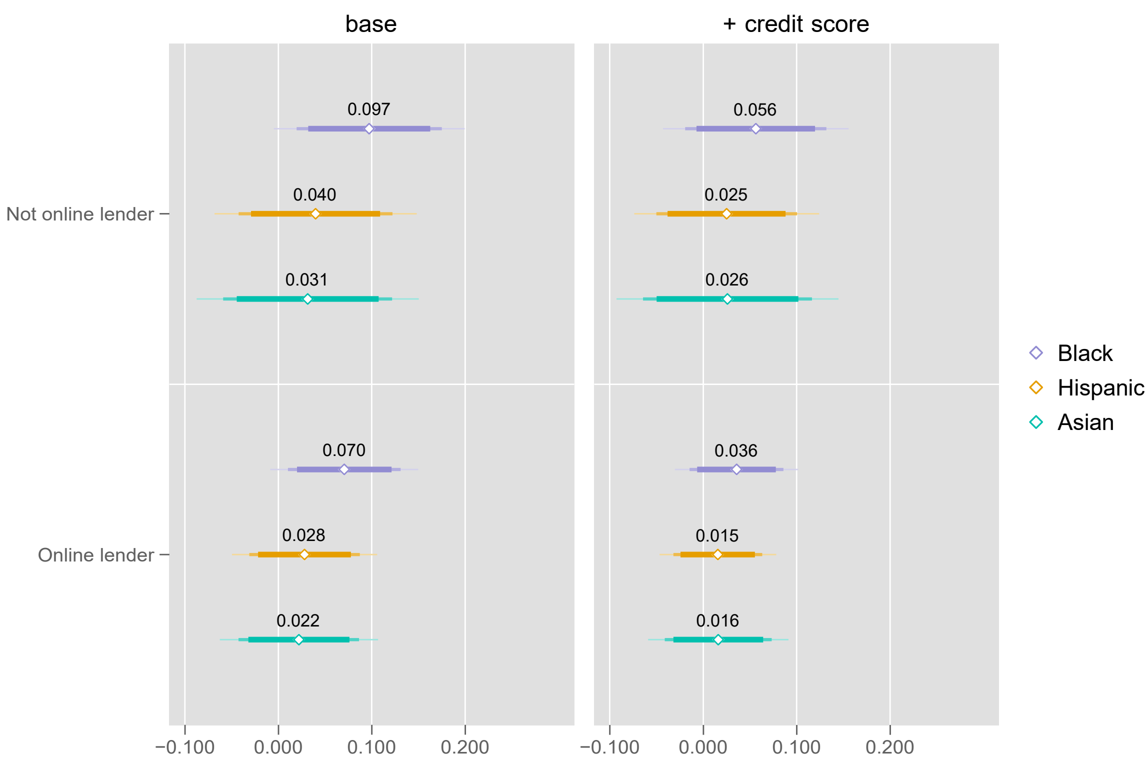
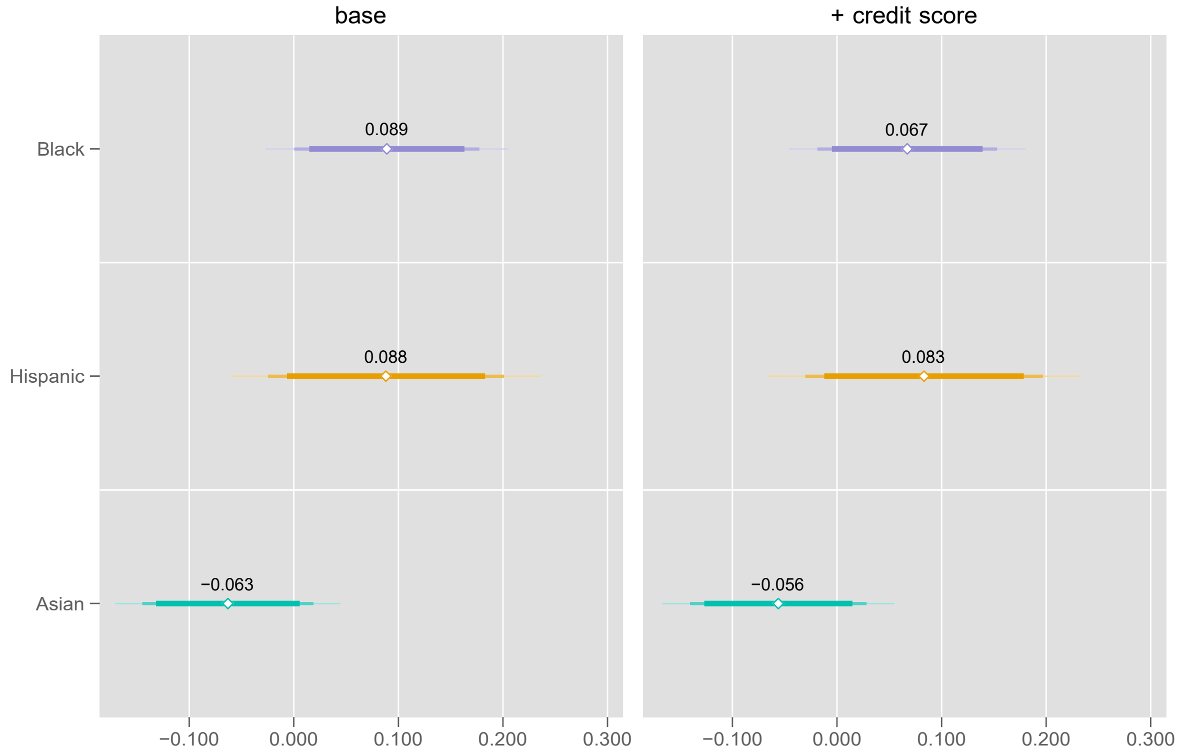


Figure 3: Predicted probabilities of being denied financing, 2016-2019, by an online lender relative to white-owned firms. Probabilities are reported as average marginal effects. Source: Authors' calculations, Federal Reserve Banks, 2016-2020 Small Business Credit Survey.



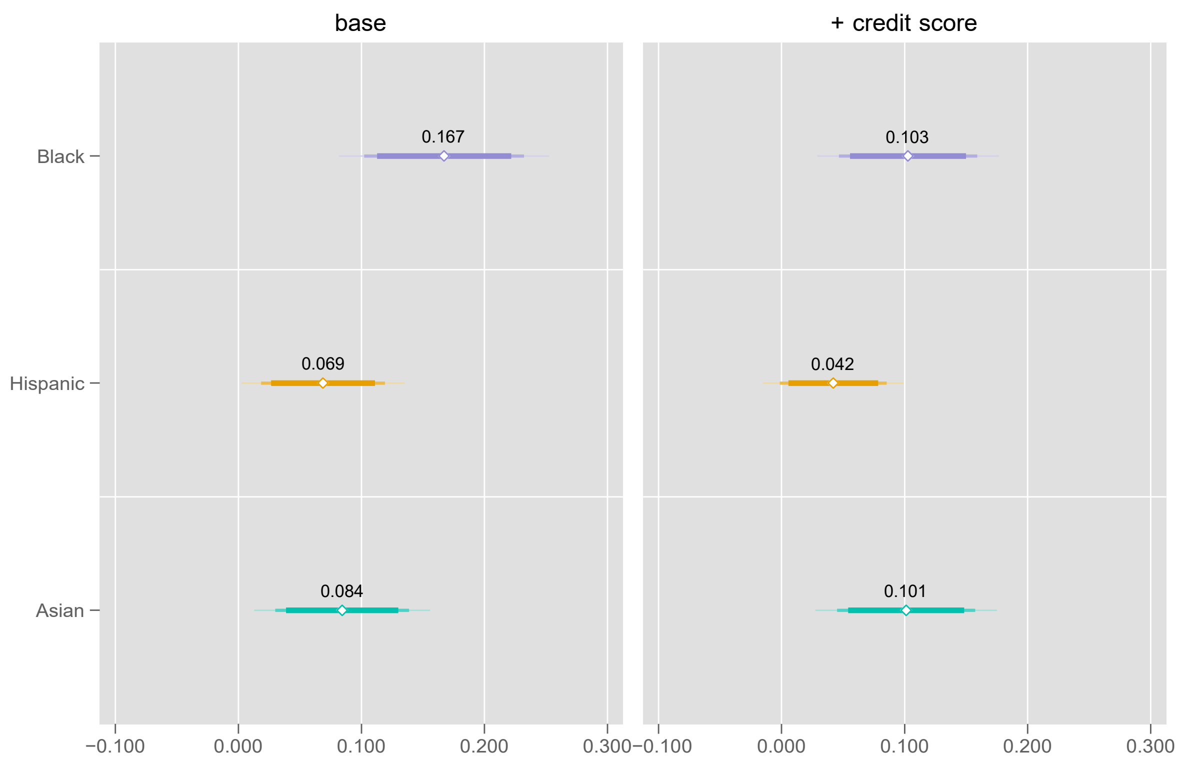


Figure 4: Predicted probabilities of (Top) being denied conventional financing and (Bottom) being discouraged from applying relative to white-owned firms, 2020. Probabilities are reported as average marginal effects. Source: Authors' calculations, Federal Reserve Banks, 2016-2020 Small Business Credit Survey.

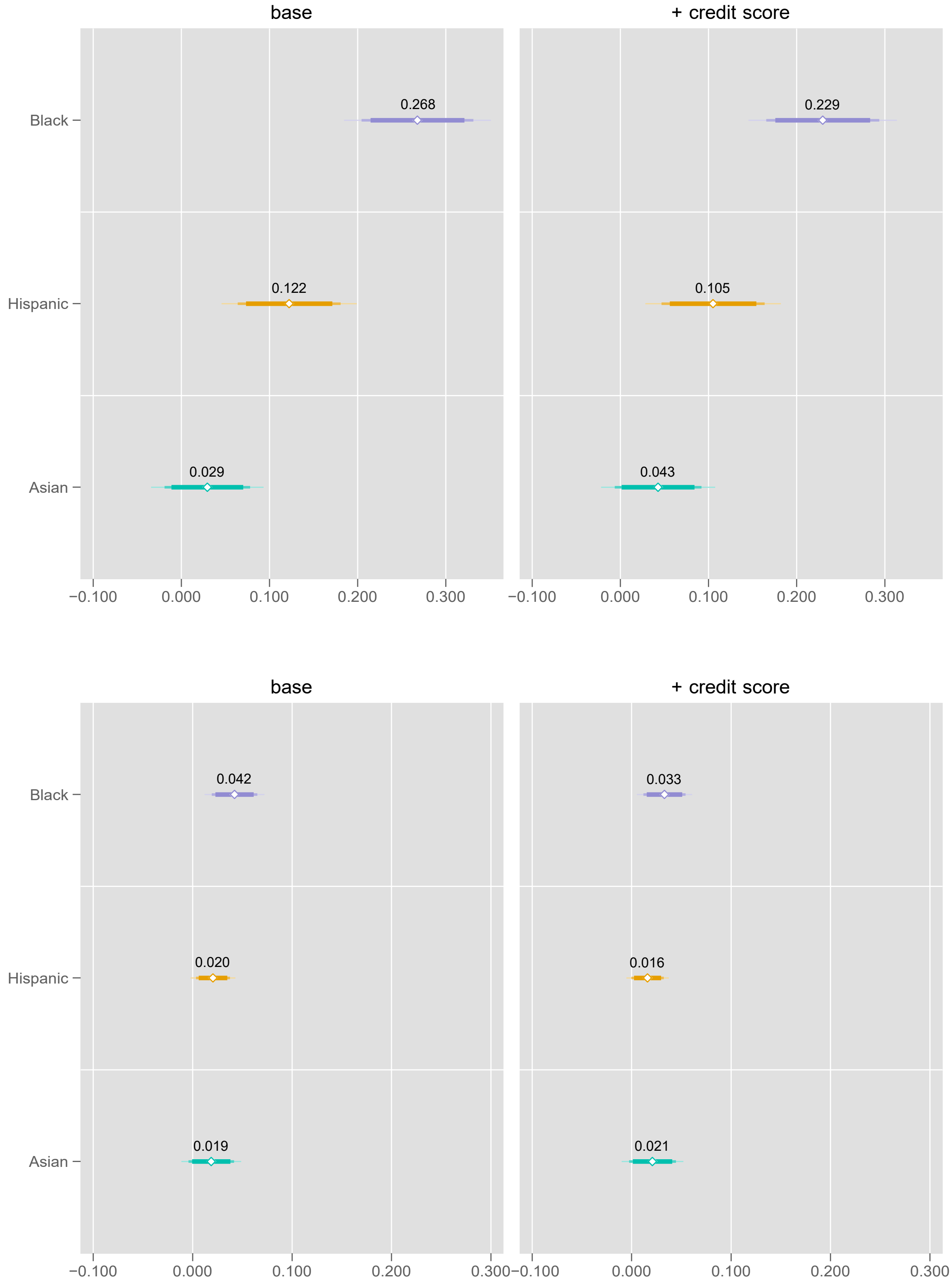


Figure 5: Predicted probabilities of (Top) being less than fully approved for PPP financing and (Bottom) being discouraged from applying for PPP relative to white-owned firms, 2020. Probabilities are reported as average marginal effects. Source: Authors' calculations, Federal Reserve Banks, 2016-2020 Small Business Credit Survey.

Table A1: Pre-pandemic financing with businesses characteristics: Denial and discouragement

	Denials		Discouragement	
	Base	+ Credit Score	Base	+ Credit Score
# Employees	-0.008**	-0.007*	0.004	0.005
	(0.004)	(0.004)	(0.005)	(0.004)
# Employees^2	0.000**	0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
3-5 years	-0.117	-0.136	0.067	0.064
	(0.147)	(0.150)	(0.136)	(0.145)
6-10 years	-0.034	-0.030	0.069	0.082
	(0.152)	(0.152)	(0.130)	(0.140)
11-15 years	-0.233	-0.214	-0.068	0.014
	(0.174)	(0.177)	(0.146)	(0.155)
16-20 years	-0.563***	-0.497**	-0.290*	-0.154
	(0.199)	(0.203)	(0.168)	(0.169)
21+ years	-0.429**	-0.392**	-0.608***	-0.446***
	(0.169)	(0.170)	(0.140)	(0.144)
Rev $100K-$1M	-0.467***	-0.435***	-0.213**	-0.172
	(0.132)	(0.135)	(0.108)	(0.114)
Rev $1M-$10M	-1.029***	-0.925***	-0.657***	-0.439***
	(0.163)	(0.164)	(0.142)	(0.152)
Rev $10M+	-1.222***	-1.162***	-0.751**	-0.419
	(0.346)	(0.345)	(0.380)	(0.380)
Profitable	-0.390***	-0.306***	-1.056***	-1.031***
	(0.093)	(0.095)	(0.088)	(0.090)
Female	-0.126	-0.160	0.080	0.066
	(0.098)	(0.100)	(0.086)	(0.093)
Veteran	-0.222	-0.222	-0.121	-0.107
	(0.139)	(0.143)	(0.144)	(0.154)
Black	0.456***	0.299**	0.981***	0.472***
	(0.126)	(0.133)	(0.121)	(0.147)
Asian	-0.032	-0.062	0.302**	0.314**
	(0.188)	(0.194)	(0.150)	(0.158)
Native Amer.	0.592*	0.431	-0.130	-0.066
	(0.326)	(0.320)	(0.315)	(0.307)
Hispanic	0.295*	0.196	0.493***	0.216
	(0.154)	(0.152)	(0.130)	(0.150)
Medium risk		0.563***		1.734***
		(0.110)		(0.111)
High risk		1.204***		3.129***
		(0.173)		(0.198)
Did not respond		0.532***		0.043
		(0.111)		(0.100)
Observations	9745	9745	14275	14275

Standard errors in parentheses
Results reported are for 2016-2019. Select variables shown. All models include the following variables: employee size, employee size squared, age of firm, revenue size, profit, revenue growth, industry of business, veteran ownership, female ownership, race of ownership. For models that include credit risk, risk is determined by the self-reported business credit score or personal credit score ofthe owner, depending on which is used to obtain financing for the business. If the firm uses both, the higher risk rating is used. Lowcredit risk is a 80-100 business score or 720+ personal credit score. Medium credit risk is a 50-79 business credit score or a 620-719personal credit score. High credit risk is a 1-49 business credit score or less than a 620 personal credit score.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Pandemic financing with businesses characteristics: Denial and discouragement

	Denials		Discouraged	
	Base	+ Credit Score	Base	+ Credit Score
# Employees	-0.017**	-0.015*	-0.010	-0.003
	(0.008)	(0.009)	(0.010)	(0.010)
# Employees^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
3-5 years	-0.043	0.043	-0.126	-0.194
	(0.260)	(0.266)	(0.221)	(0.232)
6-10 years	-0.350	-0.275	-0.230	-0.208
	(0.252)	(0.251)	(0.209)	(0.225)
11-15 years	-0.588**	-0.485*	0.084	0.051
	(0.288)	(0.286)	(0.221)	(0.230)
16-20 years	-0.554*	-0.461	-0.558**	-0.527*
	(0.304)	(0.309)	(0.250)	(0.270)
21+ years	-0.685***	-0.595**	-0.570***	-0.387*
	(0.256)	(0.258)	(0.204)	(0.223)
Rev $100K-$1M	-0.383	-0.426	-0.130	-0.111
	(0.333)	(0.335)	(0.229)	(0.235)
Rev $1M-$10M	-0.519	-0.527	-0.041	0.064
	(0.342)	(0.344)	(0.252)	(0.263)
Rev $10M+	-0.648	-0.632	-0.289	-0.226
	(0.499)	(0.497)	(0.517)	(0.515)
Profitable	-0.193	-0.134	-0.777***	-0.701***
	(0.160)	(0.162)	(0.130)	(0.135)
Female	0.128	0.139	0.097	0.028
	(0.167)	(0.171)	(0.129)	(0.134)
Veteran	0.131	0.161	0.277	0.235
	(0.275)	(0.263)	(0.223)	(0.244)
Black	0.488**	0.383	1.241***	0.922***
	(0.229)	(0.235)	(0.192)	(0.208)
Asian	-0.429	-0.384	0.733***	0.911***
	(0.315)	(0.321)	(0.203)	(0.214)
Native Amer.	-0.302	-0.374	0.071	0.049
	(0.648)	(0.682)	(0.487)	(0.529)
Hispanic	0.484*	0.467	0.621***	0.437**
	(0.291)	(0.301)	(0.200)	(0.208)
Medium risk		0.415**		1.326***
		(0.188)		(0.170)
High risk		1.190***		2.398***
		(0.323)		(0.289)
Did not respond		0.246		-0.097
		(0.219)		(0.164)
Observations	2231	2231	5015	5015

Standard errors in parentheses
Select variables shown. All models include the following variables: employee size, employee size squared, age of firm, revenue size, profit, revenue growth, industry of business, veteran ownership, female ownership, race of ownership, YoY change in state unemployment rate, census division, and the location of the business in a low-, moderate-, or middle-income zip code. For models thatinclude credit risk, risk is determined by the self-reported business credit score or personal credit score of the owner, depending on which is used to obtain financing for the business. If the firm uses both, the higher risk rating is used. Low credit risk is a 80-100 business score or 720+ personal credit score. Medium credit risk is a 50-79 business credit score or a 620-719 personal credit score. High credit risk is a 1-49 business credit score or less than a 620 personal credit score.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: PPP financing with businesses characteristics: Partial approval and discouragement

	Partial approval		Discouraged	
	Base	+ Credit Score	Base	+ Credit Score
# Employees	-0.017***	-0.015**	-0.108***	-0.104***
	(0.006)	(0.006)	(0.035)	(0.035)
# Employees^2	0.000**	0.000**	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
3-5 years	-0.134	-0.136	-0.269	-0.276
	(0.156)	(0.157)	(0.232)	(0.232)
6-10 years	-0.194	-0.149	-0.188	-0.139
	(0.152)	(0.153)	(0.257)	(0.255)
11-15 years	-0.167	-0.120	0.194	0.230
	(0.161)	(0.162)	(0.287)	(0.284)
16-20 years	-0.413**	-0.356**	0.298	0.344
	(0.179)	(0.178)	(0.347)	(0.347)
21+ years	-0.572***	-0.479***	-0.354	-0.282
	(0.144)	(0.144)	(0.287)	(0.285)
Rev $100K-$1M	-0.497***	-0.490**	-1.026***	-1.043***
	(0.190)	(0.194)	(0.227)	(0.228)
Rev $1M-$10M	-0.730***	-0.696***	-1.825***	-1.793***
	(0.201)	(0.203)	(0.339)	(0.342)
Rev $10M+	-1.337***	-1.313***	-2.812***	-2.821***
	(0.333)	(0.329)	(1.082)	(1.086)
Profitable	-0.146	-0.113	-0.464***	-0.410**
	(0.091)	(0.092)	(0.180)	(0.178)
Female	-0.002	-0.006	-0.155	-0.176
	(0.087)	(0.087)	(0.181)	(0.185)
Veteran	-0.133	-0.120	-0.107	-0.115
	(0.187)	(0.190)	(0.345)	(0.360)
Black	1.313***	1.165***	0.988***	0.832***
	(0.145)	(0.149)	(0.211)	(0.220)
Asian	0.174	0.253*	0.534*	0.585**
	(0.142)	(0.143)	(0.286)	(0.286)
Native Amer.	0.656	0.720*	1.889***	1.803***
	(0.412)	(0.399)	(0.430)	(0.426)
Hispanic	0.655***	0.582***	0.573***	0.468**
	(0.146)	(0.152)	(0.212)	(0.218)
Medium risk		0.689***		0.785***
		(0.116)		(0.215)
High risk		1.013***		0.960***
		(0.240)		(0.360)
Did not respond		0.038		0.370*
		(0.104)		(0.216)
Observations	6827	6827	8456	8456

Standard errors in parentheses
Select variables shown. All models include the following variables: employee size, employee size squared, age of firm, revenue size, profit, revenue growth, industry of business, veteran ownership, female ownership, race of ownership, YoY change in state unemployment rate, census division, and the location of the business in a low-, moderate-, or middle-income zip code. For models thatinclude credit risk, risk is determined by the self-reported business credit score or personal credit score of the owner, depending on which is used to obtain financing for the business. If the firm uses both, the higher risk rating is used. Low credit risk is a 80-100 business score or 720+ personal credit score. Medium credit risk is a 50-79 business credit score or a 620-719 personal credit score. High credit risk is a 1-49 business credit score or less than a 620 personal credit score.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$