Can Fintech Benefit Minority-owned Small Businesses? Evidence from the Paycheck Protection Program

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Abstract

Using a linked database on a large national-wide sample of restaurants from Yelp and on Paycheck Protection Program (PPP) loans in the 2020 and 2021 waves, we study how fintech lenders can benefit minority-owned small businesses. We document that the customer rating gap between minority- and non-minority-owned restaurants is smaller for fintech lenders compared with non-fintech lenders. In a simple two-sided matching game model, a smaller difference in customer ratings indicates that minority-owned restaurants are less undervalued when matched with fintech than with non-fintech lenders. We find that lending relationships, the business capital of borrowers, and attention and resources allocated to the region by lenders contribute to the difference between minority- and non-minority-owned small businesses. We do not find a similar pattern for first-time banks, community development financial institutions, or credit unions. A higher preference for quick loan approval of minority-owned businesses also cannot explain the racial disparity we document. Our results suggest that there are systematic biases in the traditional loan distribution channel which can be at least partially addressed by fintech lenders.

Keywords: Racial Discrimination, Minority-owned Businesses, Paycheck Protection Program, Small Business Lending, Bank Lending, Nonbank Lending, Fintech, Government Lending Program

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1. Introduction

There is a huge debate among legislators, regulators, financial institutions, and small business advocates on whether to allow fintech lenders to provide loans in government funding programs, such as SBA programs. On the one hand, fintech lenders have the advantages of high capacity, convenience (Fuster et. al. (2019)), and using alternative data (Berg et. al. (2020)), and take a large share of the small business credit market.[1] Allowing fintech lenders to participate in the government programs can provide easier access to small business owners. On the other hand, fintech lenders may have hidden costs, risks arising from complex loan structures, and privacy concerns (Lipman and Wiersch (2019)), which may impose instability in the financial system.

In this paper, we investigate an important question regarding the impact of fintech lending on small businesses that might be overlooked. Can fintech lenders extend the scope of borrower types, especially for minority-owned businesses? More specifically, we ask whether fintech lenders cover a certain segment of minority-owned businesses who find themselves harder to get credit access than otherwise similar non-minority-owned businesses. Given that government small business programs usually have the intention to help disadvantaged groups, understanding such a question is crucial.

Despite that minority-owned businesses are a rapidly growing segment of small businesses[2], they face structural barriers in getting credit access. Even in the full government-guaranteed loan program, the Paycheck Protection Program (PPP), minority-owned businesses do not have the same lending outcome as non-minority-owned businesses in the aspects of loan amounts (Atkins, Cook, and Seamans (2021); Fairlie and Fossen (2021)), take-up rate (Chernenko and Scharfstein (2021); Wang and Zhang (2020)), and lender types (Erel and Liebersohn (2020); Howell et. al. (2021)).

In particular, Erel and Liebersohn (2020) find that on the zip-code level, fintech lenders are more heavily used in neighborhoods with higher minority shares. Howell et. al. (2021) find that fintech lenders make a larger share of their PPP loans to Black-owned businesses. These

[1] According to the Federal Reserve Banks' Small Business Credit Survey (SBCS), nearly one-third (33 percent) of small businesses that applied for credit in 2019 sought it from an online lender (SBCSa, 2021), especially for non-employers (SBCSb, 2021) and minority racial groups (SBCSc, 2021).

[2] Minority-led small business increases at a rate of 11% compared to white-owned firms (1%) between 2014 and 2016 (Toussaint-Coumeau and Williams (2020)).

observations pose a natural follow-on question which we address in this paper. Are fintech lenders more popular among minority-owned businesses simply because of ex-ante differences between minority- and non-minority-owned businesses, or because minority-owned businesses face more frictions when accessing the traditional credit market?

Answering such a question is challenging at a normal time. Firstly, the segment of minority-owned businesses that face a higher barrier in the traditional small business loan market tends to be hidden in the observed data. We cannot distinguish between whether those minority-owned businesses do not have the intention to participate in the loan market, or because they cannot get the same valuation with traditional lenders as their non-minority counterparts, and therefore they have no choice but to seek other informal financing sources, such as family money (Bates (1997)). Even with application and rejection data, the prerequisite is that minority-owned businesses apply for the loan in the first place.

Secondly, at a normal time, many confounding factors can affect the matching outcome between lenders and borrowers in equilibrium. For example, fintech loans tend to have more flexible loan terms which might be a reason for attracting different types of borrowers. It may also be possible that fintech lenders target a particular group of minority borrowers on purpose, and therefore we observe a different matching pattern between minority borrowers with fintech and non-fintech lenders. In addition, borrowers might apply to fintech and non-fintech lenders at different firm development stages and might coincide with a distinct pattern for minority and non-minority borrowers.

The PPP program offers a good real-world laboratory to study the question for several reasons. Firstly, the extremely low interest rate level and the possibility of forgiveness provide strong incentives for borrower participation. Admittedly, some borrowers might be rejected after the loan application, but the survey results in Bartik et. al. (2021) suggest that inability to submit an application accounts for two-thirds of the loan denials and in total only 8% of the loan applications are rejected by the SBA. The question then becomes the matching between different types of borrowers and lenders. If we observe a different set of borrowers matched with fintech and non-fintech lenders, it implies that there exist disparities in the underlying valuation of the lender-borrower matches.

Secondly, as Covid-19 is mainly a health shock, all small businesses, regardless of their financial or operational situation before the Covid-19 crisis, have a similar credit demand.

Moreover, the loan terms are designed by the SBA and are uniform for all loans to a large degree[3]. These special regulation features of the PPP loans control for variation from the demand-side and loan terms, leaving the borrower and lender types as the main sources of heterogeneity.

In particular, we focus on one of the most Covid-vulnerable sectors, the *Food Services and Drinking Places* sector, and use the customer ratings to gauge the difference in the minority-non-minority gap between fintech and non-fintech lenders (fintech-minority double-difference for short). Focusing on the restaurant sample offers several advantages. Firstly, it provides a proxy for minority-owned businesses for a representative sample. One limitation of the PPP loan-level data is that the information on race and ethnicity of loan recipients is missing for almost 90% of the sample. We address this challenge by using the food type information on yelp.com as a proxy for the race and ethnicity information of the restaurant owners. Overall, as we shall present in detail, our racial group measures work reasonably well. Secondly, almost all restaurants are eligible for the PPP program and therefore there is no additional variation imposed by regulatory eligibility.[4] Thirdly, the restaurant industry is among the most Covid-19 vulnerable industries and thus can help us to understand how the Covid-19 crisis affect small businesses.

We mainly rely on the *FinTech Company List* published on the SBA official website (sba.gov) to identify fintech lenders in our sample. Fintech lenders are the largest category of alternative lenders in the PPP program. As a comparison, around 9.65% of the borrowers have a loan from fintech lenders; around 3.48% of the borrowers have a loan from credit unions which is the second-largest type of bank alternatives in our sample. Figure 1 shows that in the 2021 wave of the PPP program, non-fintech lenders deliver more loans to non-minority-owned businesses compared with minority-owned businesses (Figure 1(a)). In contrast, for fintech lenders, there is no clear gap between the loan amounts disbursed to minority- and non-minority-owned businesses (Figure 1(a)). This provides a first look at the importance of fintech lending for minority-owned businesses.

We first develop a simple transferable utility matching game model where the payoff function can be either race-neutral or race-biased. Our model provides several possible reasons for a higher likelihood of fintech usage by minority-owned businesses. Even in a race-neutral scenario, an ex-

[3] Interest rate is fixed at 1% for all loans. Loans issued prior to June 5, 2020, have a maturity of two years. Loans issued after June 5, 2020, have a maturity of five years.

[4] For most industries, the eligibility requirement is either meeting the SBA size standards for small businesses or less than 500 employees. For the industries with a NAICS code that begins with 72 (Accommodations and Food Services), the business is eligible for the PPP as long as the number of employees is fewer than 500 at each location.

ante difference in the average rating levels or the share of borrowers possessing lending relationships can be translated into a difference in fintech usage rate.

Firstly, the self-selection effect that higher-rated borrowers choose fintech lenders more leads to a higher rating level on average for borrowers matched with fintech lenders than with non-fintech lenders. Under this case, if minority-owned restaurants have higher ratings on average, our model predicts that they are more likely to be matched with fintech than non-fintech lenders. Secondly, lending relationships may have an effect that lower-rated borrowers with lending relationships crowd out higher-rated borrowers from banks to fintech lenders. Combined with higher rating levels on average for minority-owned restaurants, we will also see a higher rate of fintech usage among minority-owned restaurants. Thirdly, if a smaller share of minority-owned restaurants possess lending relationships, they will suffer relatively more from the crowding-out effect of lending relationships, and be pushed disproportionally more towards fintech lenders.

However, only in the race-biased equilibrium, we observe a *Double-Difference* in rating levels. In the race-neutral case, the difference in the rating levels of minority and non-minority borrowers is the same for fintech and non-fintech lenders. In contrast, when there is a difference in the underlying valuation for the minority and non-minority borrowers of the same rating-level who are matched with fintech and with non-fintech lenders (i.e., racial disparity in borrower-lender valuation), the equilibrium features a double-difference in rating levels.

In reality, there can be several sources for such a difference in the value of fintech lenders compared to non-fintech lenders between the minority and non-minority borrowers. For example, the less bureaucratic process and fewer human contacts in the loan application when using fintech lenders may be more beneficial for minority borrowers due to language barriers. It is also possible that minority borrowers might have had more bad experiences before with banks and therefore have a higher expectation from new technology-oriented lenders. On the lender side, fintech lenders may have a higher value on diversity as they tend to advertise themselves as the angel for underserved small businesses.

We start by providing a graphical illustration of the minority and fintech shares of PPP loans across the states. The variation in the minority loan shares across states is very limited in both years, which implies that comparing the geographic variation in minority shares per se might underestimate the minority-non-minority disparities in the PPP program. Moreover, the variation in fintech shares does not coincide with minority share variation, suggesting that fintech lenders

are not matched with minority- and non-minority-owned businesses with the same propensity. There is potentially an underlying difference between the segment of minority-owned businesses that are matched with fintech and with non-fintech lenders.

Empirically, we first provide evidence that minority-owned businesses are more likely to use fintech lenders, which is consistent with the findings in the exiting papers on the PPP program (Erel and Liebersohn (2020); Howell et. al. (2020)). We find a positive coefficient for all the three main racial groups: African-Americans, Asians and Pacific Islanders (Asians henceforth), and Hispanics. The positive relationship between minority borrowers and fintech lenders is even stronger in 2021, probably due to the experience passing in the minority communities and advertisements of fintech lenders.

More importantly, we document the existence of a negative double-difference in rating levels. We find that the difference in customer ratings between minority- and non-minority-owned restaurants is smaller for fintech lenders compared with non-fintech lenders. The results are robust when we restrict to a matched sample using the state where the business locates, business type, food price range, and employment size as matching covariates. We provide further evidence on the heterogeneity among lenders by looking at the biggest four fintech lenders, Cross River Bank, Kabbage, Square, and Paypal, and the largest seven banks, JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. We find that fintech lenders have a negative minority-non-minority rating gap and banks, especially for relative "small" big banks Truist, PNC, and TD Bank, have a positive rating gap, which is consistent with our main regression results.

To further study what are the underlying sources of racial disparities in small businesses lending, we test the several important predictions of our model. Firstly, as discussed above, the combination of self-selection/crowding-out effects and a difference in rating level distributions across racial groups can result in a different rate of fintech usage for minority- and non-minority-owned businesses. However, we do not find systematic evidence supporting this self-selection explanation for the higher likelihood of fintech usage among minority-owned restaurants. In a similar vein, the combination of the crowding-out effect of borrowers with lending relationships and a higher average rating of minority-owned businesses has little empirical support at least in our sample. Therefore, this more accidental reason for the higher popularity of fintech lenders among minority-owned businesses is unlikely to drive the racial disparities in the PPP program documented in the literature and this paper.

Secondly, and more interestingly is that if a smaller share of minority-owned restaurants have lending relationships, the minority-owned restaurants are relatively more affected by the crowding-out effects of restaurants with lending relationships and use fintech lenders disproportionally more. Our empirical evidence supports this hypothesis as we find that minority-owned restaurants are less likely to have borrowed SBA 7(a) or 504 loans and borrow fewer and smaller amounts of loans during 2009-2019. This channel speaks to one source of frictions in the small business lending market that comes from racial inequality in lending relationships.

Thirdly, our model predicts that a larger difference in the tech-savviness between the minority and non-minority borrowers means a larger racial disparity in the fintech-minority double difference in rating levels. Similarly, the racial disparity is also positively related to the difference in the value of lending relationships between the minority and non-minority borrowers. As there is no good measure of tech-savviness or value of lending relationship, we cannot directly test these predictions. Instead, we use some factors that affect the tech-savviness gap or the lending-relationship-value gap as a way to indirectly test these predictions. Moreover, investigating these factors speaks directly to the sources of frictions that lead to the racial disparity in the small business lending market. We find that the business capital of borrowers can alleviate the racial disparities, and less attention allocated to each region of lenders, proxied by a larger relative geographic lending scope, aggravates the racial disparity.

We rule out several non-technology-related features of fintech lenders by studying other lender classifications. We do not find similar patterns for first-time banks, non-federally insured financial institutions, S&Ls, credit unions, CDFIs/CDCs. In addition, we rule out the alternative explanation that minority borrowers turn to fintech lenders because they enjoy the speed of fintech lending. At least in 2020, we find that minority borrowers using fintech lenders have a later approval date.

Overall, our findings suggest that there exist systematic biases and blind spots in the traditional small business lending market. In the PPP program, fintech lenders are reached by a different group of minority borrowers than non-minority borrowers in terms of ratings. This implies that minority borrowers do not have the same valuation when accessing the credit market and turning to fintech lenders can be a way to supplement the funding channels.

Our study provides one benefit of introducing fintech lenders into government loan programs that might be overlooked, given those minority borrowers tend to be hidden in the data in normal

time. Whether governments should extend credit access to those minority-owned businesses is a normative question. Admittedly, these minority-owned businesses are of lower rating levels and are likely to have lower revenue (Luca (2016)). However, they are part of the fabric of their communities, employing local residents and supporting civic causes. Moreover, as suggested by the existing literature (Krishnan, Nandy, and Puri (2015); Brown and Earle (2017)), SBA loans have positive effects on firm growth and productivity. The minority-owned business that are previously excluded from the government loan programs can improve their operational and financial performance with the improvement in credit access.

Our paper adds to the literature on the racial disparity in the small business lending market. In particular, early researches on the PPP program show the existence of uneven loan distribution (Atkins, Cook, and Seamans (2021); Fairlie and Fossen (2021); Wang and Zhang (2020)), and how fintech lender may substitute to the traditional lenders (Erel and Liebersohn (2020)). Our paper is most closely related to concurrent independent researches of Chernenko and Scharfstein (2021) and Howell et. al. (2021) that study the racial disparity using loan-level information and additional data. Our paper differs from theirs by focusing on fintech lenders and providing an understanding of the existence and sources of economic racial discrimination.

More broadly, our research contributes to the recent literature on the impact of fintech lending on racial discrimination (Bartlett et. al. (2021); Fuster et. al. (forthcoming); D'Acunto et. al. (2020)). Our paper adds to the literature by using the PPP program as a laboratory to show that minority- and non-minority-owned businesses face different level valuation frictions, which can be mitigated at least partially by fintech lenders. Our paper is also related to the literature on the financial inclusion role of fintech (Jagtiani and Lemieux (2018); Mills and McCarthy (2016)).

2. A Simple Model of The Borrower-Lender Matching Game

In this section, we present a simple transferable utility matching game model (Azevedo and Hatfield 2018) to illustrate the matching process between borrowers and lenders in the PPP program. The main purpose of the model is to show that we can use an observed borrower-related variable, such as the customer ratings of the restaurant, to gauge the taste-based discrimination in the valuation of the lender-borrower matches between the minority and non-minority borrowers.

The main predictions of our model are the following. Firstly, even the incentives of direct statistical discrimination on the lender side are ruled out by the special feature of the full government-guaranteed in the PPP program (Atkins, Cook, and Seamans (2021)), there might be self-selection effects such as that higher-rated borrowers are more likely to find places to borrow the PPP loan and that they are more capable to fill the application forms. Therefore, the disparity in the matching rates across different racial groups can arise from the ex-ante differences across borrowers. More importantly, taste-based racial biases further distort the allocation, featuring a fintech-bank and minority-non-minority *Double-Difference* (fintech-minority double-difference henceforth) in the rating level of matched pairs in equilibrium.

We present the basic model setup, the main results, and the intuitions behind the results here. Further details on the model assumptions, mathematical demonstrations of the equilibrium, and detailed deviations and discussions can be found in the Online Appendix D.

Model Setup. There are a group of minority borrowers with a mass of M^m and a group of non-minority borrowers with a mass of M^{nm} whose ratings follow the normal distribution $\gamma_i^m \sim N(\mu^m, \sigma^m)$, and $\gamma_i^{nm} \sim N(\mu^{nm}, \sigma^{nm})$ respectively.[5] There are a group of fintech lenders with a mass of M^f and a group of banks with a mass of M^b.

Payoff Function. The payoff function of a match between the borrower *i* and the lender *j*, $p_{i,j}(\gamma_i, \theta_{i,j})$, depends on the borrower's rating level γ_i and a lender-borrower dependent factor $\theta_{i,j}$, such as the borrower's tech-savviness and previous lending relationships between the borrower and the lender. $\theta_{i,j}$ captures the differences in the preference of borrowers for fintech lenders and banks, and the differences in the preference of lenders for minority and non-minority borrowers. $\theta_{i,j}$ is racial-neutral when we study the scenario with no taste-based discriminations. When we study the equilibrium under taste-based discriminations, $\theta_{i,j} = \theta_{i,j}^{mm}$ for minorities and $\theta_{i,j} = \theta_{i,j}^{nm}$ for non-minorities. For simplification purposes, we assume that the payoff function is increasing in the borrower's rating γ_i and of a linear functional form $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta_{i,j}$.

Matching Game. Without loss of generality, we study a 1-1 borrower-lender matching game where the borrowers choose which lender to apply for the loan and the lenders choose the set of borrowers that gives her the highest sum of transferred payoffs.[6] The borrower's payoff is the total

[5] Empirical patterns support a normal distribution of ratings.

[6] In the PPP program, observations that a borrower is granted multiple loans tend to be few. In our sample construction, we identified less than 2% of the restaurants appeared to be associated with multiple loans. We exclude those

payoff $p_{i,j}(\gamma_i, \theta_{i,j})$ minus the transferred utility if the lender of her choice also chooses to process the loan for her, and zero otherwise. The same works for the lenders.

Equilibrium. In a competitive equilibrium, incentive compatibility means any deviation from either the borrower side or the lender side cannot achieve a higher payoff.

$$p_{i,j}(\gamma_i, \theta_{i,j}) \geq p_{i,j'}(\gamma_i, \theta_{i,j'}) \; for \; j' \neq j \text{ and } p_{i,j}(\gamma_i, \theta_{i,j}) \geq p_{i',j}(\gamma_{i'}, \theta_{i',j}) \; for \; i' \in I \backslash I_j^* \quad (1)$$

Where I is the entire borrower set, and I_j^* is the optimal choice set of lender j.

We discuss three scenarios. In the first scenario, the payoff function only depends on the rating level of the borrower. In the second scenario, the payoff function depends on the rating level of the borrower as well as a race-neutral lender-borrower factor $\theta_{i,j}$. In the third scenario, the payoff function depends on the rating level of the borrower and a race-biased lender-borrower factor $\theta_{i,j}^{m/nm}$.

Scenario 1 – (Benchmark) Race-Neutral Payoff. We first study the benchmark case where the payoff function only depends on the borrower's rating level and therefore is race-neutral ($p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$). We have a unique symmetric equilibrium where fintech lenders and banks are matched with borrowers whose rating is above the same threshold $\underline{\gamma}$ for both the minority and non-minority groups where $\underline{\gamma}$ is determined by

$$\delta M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m) dx + \delta M^{nm} \int_{\underline{\gamma}}^{\infty} f(x, \mu^{nm}, \sigma^{nm}) dx = M^f$$

$$(1-\delta) M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m) dx + (1-\delta) M^{nm} \int_{\underline{\gamma}}^{\infty} f(x, \mu^{nm}, \sigma^{nm}) dx = M^b$$

Where $f(\mu^m, \sigma^m)$ and $f(\mu^{nm}, \sigma^{nm})$ are the density functions of the rating distribution for the minority and non-minority borrowers respectively.

[INSERT FIGURE 2 AROUND HERE]

observations from our analysis sample. On the lender side, as we study the average difference between the fintech lenders and banks, a 1-m matching game can be easily captured, without affecting the main results, by combining multiple lenders in the same type into one lender.

One thing to notice is that the percentage of matched borrowers, i.e. who gain a loan, can vary across racial groups if the rating distribution functions are different. Figure 2 shows the rating density functions for African Americans, Asians, Hispanics, and non-minority borrowers in our sample. The rating distributions of Asians and Hispanics appear to have the same mean as the non-minority borrowers, and the rating distribution of African Americans has a larger mean.[7] A higher (lower) mean of the rating distribution results in a higher (lower) percentage of matched borrowers in equilibrium. Therefore, the ex-ante difference in the rating distribution across racial groups results in a difference in the percentage of borrowers getting the PPP loan in equilibrium, which is aligned with statistical discrimination.

Scenario 2 – Race-Neutral Borrower-Lender-Specific Payoff. In the second scenario, the payoff function depends on the rating of the borrower as well as a *race-neutral* borrower-lender-specific factor $\theta_{i,j}$.

Firstly, we consider the possibility that higher-rated borrowers are tech savvier and therefore have a higher payoff when matched with fintech lenders than with banks. Notably, however, we assume that the minority and non-minority borrowers of the same rating level have the same additional preference for fintech lenders to banks. In this case, we have a race-neutral equilibrium in terms of rating levels of minority and non-minority borrowers matched with fintech lenders and with banks.

However, due to the self-selection of higher-rated borrowers into fintech lenders, the average rating of borrowers matched with fintech lenders is higher than banks. Moreover, the model predicts that a combination of higher ratings on average for minority borrowers and the self-selection of higher-rated borrowers into fintech lenders can lead to an outcome that minority borrowers are more likely to be matched with fintech lenders, which is the main difference from the benchmark case. As the same in the benchmark case, we have the prediction of a higher matching rate for the higher-rated borrowers.

Secondly, we discuss the situation where the payoff functions are different for borrower-bank matches with and without previous lending relationships but in a race-neutral way. Previous lending relationships play a crucial role in the PPP program (Li and Strahan (2020)). There could

[7] We also present regression results in Online Appendix B Table B2 showing that Africans have higher ratings and Asians and Hispanics have lower ratings on average, controlling for other restaurant features and city times month fixed effects.

be several types of the additional value of lending relationships. For example, on the lender side, helping existing customers to survive the crisis may alleviate the debt overhang problems and lower down the default risks on existing loans. On the borrower side, the existing profile of the borrower can navigate the application procedure more smoothly.

In this case, we still have a race-neutral equilibrium in terms of rating levels. However, because of the additional utility from the lending relationship, the marginal borrower with lending relationships is of a lower rating level than the marginal borrower without lending relationships. This crowds out some of the higher-rated borrowers without lending relationships from banks to fintech lenders, which results in a higher average rating level for borrowers matched with fintech lenders than with banks. In addition, if a smaller mass of minority borrowers have lending relationships or if minority borrowers are of a higher rating level on average, there are relatively more matches with fintech lenders among minority borrowers compared with non-minority borrowers in equilibrium.

Scenario 3 – Race-Biased Borrower-Lender-Specific Payoff. In the third scenario, the payoff function depends on the rating of the borrower as well as a *race-biased* borrower-lender-specific factor $\theta_{i,j}^{m/nm}$.

Firstly, we study the tech-savviness case where the additional utility gain when matched with fintech lenders is race-biased. As the same in the race-neutral case, the additional utility from technology results in a higher matching threshold in terms of rating levels for fintech lenders than for banks. Unlike in the race-neutral case, the equilibrium is race-asymmetric in terms of the matching thresholds of fintech lenders. The key intuition is that because the racial group of borrowers who have a higher value for fintech lenders are willing to transfer a higher share of the total payoff to the lenders, the matching threshold of fintech lenders is smaller for that racial group of borrowers. Proposition 1 presents this result. The formal mathematical expression of the competitive equilibrium can be found in the Appendix.

Proposition 1

In the race-biased tech-savviness case, the matching thresholds for the matches of minority-fintech, non-minority-fintech, minority-bank, and non-minority-bank in equilibrium satisfy,

$$\underline{\gamma_{mf}} = \frac{\theta^{nm}}{\theta^{m}} \underline{\gamma_{nmf}}$$

$$\underline{\gamma_{mb}} = \underline{\gamma_{nmb}}$$

■

Proof in the Appendix.

Proposition 1 implies that when minority borrowers are tech savvier than non-minority borrowers with the same rating level ($\theta^m > \theta^{nm}$), the matching threshold with fintech lenders is lower for minority borrowers than for non-minority borrowers ($\underline{\gamma_{mf}} < \underline{\gamma_{nmf}}$). This has two important implications. First, , a lower matching threshold for minority-fintech matches results in a relatively larger share of minority borrowers than non-minority borrowers using fintech lenders even without a difference in the underlying rating distribution. Second, a lower matching threshold for minority-fintech matches implies a negative fintech-minority *Double-Difference* in the rating levels of the marginal borrower. In addition, the negative double-difference in the rating levels of the marginal borrower can be translated into a negative double-difference in the expected mean of rating levels of matched pairs. Corollary 1 presents this result.

Corollary 1

The fintech-minority *Double-Difference* in the matching thresholds is *negative* (*positive*) when minority borrowers compared with non-minority borrowers have a *higher* (*lower*) value of matches with fintech lenders.

$$\left(\underline{\gamma_{mf}} - \underline{\gamma_{nmf}}\right) - \left(\underline{\gamma_{mb}} - \underline{\gamma_{nmb}}\right) \lesseqgtr 0 \; if \; \theta^m \gtreqless \theta^{nm}$$

Suppose that the underlying distribution is the same for minority and non-minority borrowers, i.e., $\mu^m = \mu^{nm} = \mu$ and $\sigma^m = \sigma^{nm} = \sigma$, then the fintech-minority double difference in the conditional expectation of the rating levels equals to $\sigma\left(G\left(\frac{\underline{\gamma_{mf}}-\mu}{\sigma}\right) - G\left(\frac{\underline{\gamma_{nmf}}-\mu}{\sigma}\right)\right)$, where $G(x) = \frac{\varphi(x)}{\Phi(-x)} + \frac{\varphi(x)-\varphi(\tilde{\gamma})}{\Phi(x)-\Phi(\tilde{\gamma})}$, with $\tilde{\gamma} = \frac{\underline{\gamma_{mb}}-\mu}{\sigma}$ and $\varphi(\cdot)$ and $\Phi(\cdot)$ as the density and cumulative distribution functions of the standard normal distribution respectively.

■

Proof in the Appendix.

Consider the case that reflects the reality the best where fintech lenders only capture a small fraction of the market for both minority and non-minority borrowers, then $G(x)$ is increasing in x, and we have a negative double-difference in the expected mean of ratings for matched pairs if minority borrowers prefer fintech lenders to banks more than non-minority borrowers.

Secondly, we study the lending relationship case where the payoff function contains an additional utility component for borrower-lender matches with previous lending relationship and the additional utility differs for minority and non-minority borrowers. As a mirror situation of the tech-savviness case, the main results are similar. The equilibrium is race-asymmetry in matching thresholds for borrowers with previous lending relationships. The key intuition is that because the racial group of borrowers with a higher value for lending relationship are willing to transfer a higher share of the total payoff to lenders, the matching threshold for that racial group is smaller. For borrowers without lending relationships, because their outside option is the same, the matching threshold in equilibrium is race-independent.

Similar to in the tech-savviness case, the racial-biased borrower-lender preference also leads to a difference in the shares and average ratings of borrowers matched with different. For example, bank lending relationships may have a higher value for non-minority borrowers due to taste-based discriminations. Then our model predicts that the matching threshold with banks is lower for non-minority borrowers. This can explain the two observations we shall present in the empirical part. First, a lower matching threshold for non-minority-bank matches means a higher share of non-minority borrowers matched with banks than matched with fintech lenders, compared with minority borrowers. Second, a lower matching threshold for non-minority-bank matches implies that the minority-non-minority gap in terms of rating levels is larger for borrowers matched with banks than for borrowers matched with fintech lenders. In other words, a higher value of lending relationships for non-minority borrowers can also lead to a negative fintech-minority *Double-Difference* in rating levels.

There can be several reasons for such a difference in the preference for fintech lenders versus banks between the minority and non-minority borrowers. For example, a less bureaucratic process and fewer human contacts in the loan application when using fintech lenders may be more

beneficial for minority borrowers who may have language and culture barriers. It is also possible that minority borrowers might have more bad previous experiences with banks and therefore have a higher expectation from new technology-oriented lenders. On the lender side, it is much less costly for fintech lenders to reach any region, including those that are covered less by traditional financial institutions but with a larger minority population. Fintech lenders may also have a higher value on diversity as they tend to advertise themselves as the angel for underserved small businesses.

In summary, our model shows that the difference in the percentage of minority and non-minority borrowers gaining the PPP loan can be attributed to an ex-ante disparity in the underlying rating distributions across racial groups. Combined with a self-selection effect of higher-rated borrowers using fintech lenders, or a crowding-out effect by borrowers with previous lending relationships, the ex-ante disparity in rating distributions can further result in a difference in the likelihood of using fintech lenders versus banks between minority and non-minority borrowers. However, a fintech-minority *Double-Difference* in the rating levels can only exist when the racial bias directly enters the payoff function.

3. Data and Summary Statistics

3.1. Data sources

Our analysis relies mainly on a linked database on loan-level information of restaurants in the Paycheck Protection Program (PPP) and on the full history of customer ratings downloaded from Yelp.com. For the PPP dataset, we use the loan-level data release on March 2nd, 2021 (through sba.gov, FOIA), which is the most detailed and comprehensive version of loans of all sizes. The entire PPP dataset contains around 6.46 million loans processed by 5,593 lenders, among which around 0.37 million loans (5.77%) are for businesses in the *Food Services and Drinking Places* sector (NAICS code that equals 722). The key information we use from the PPP data includes the business name, address, state, zip code, industry, business entity type, reported employment size, and franchise name for borrowers, the formal organization name, address, city, state, and zip code for lenders. The 2021-March release covers both the 2020 wave (the first draw) and the 2021 wave

(the first and second draws)[8]. We restrict our loan sample to only first draws in order to better capture the matching between borrowers and lenders. More information on the PPP program is in the Appendix. The completeness of the 2021-March release of the PPP data enables us to address questions that have not been answered in previous studies[9], and is crucial for our study as minority-led businesses tend to have a smaller size ((U.S. Census Bureau. 2016); Fairlie and Robb (2008)) and received a smaller loan amount (Atkins, Cook, and Seamans (2021); Fairlie and Fossen (2021)).

First and foremost, to carry out our analysis we need to distinguish between traditional and fintech lenders, which we mainly rely on the *FinTech Company List* published on the SBA official website (sba.gov). We supplement the official *FinTech Company List* with information from the SBA state subsidiaries' websites and major news sources[10]. We identify 15 fintech lenders that appear in the entire PPP sample in the 2021-March release, as shown in Table A2 in the Appendix[11]. Examples of fintech lenders in our list are "Kabbage", "Square", and "Paypal". Appendix-Table A2 also reports the percentage of loans that are included in our final sample linked with yelp ratings, which indicates that our linked sample is reasonable evenly distributed across each fintech lender. We also present the comparison between our sample and the Erel and Liebersohn (2020) sample in the Online Appendix B-Table B1, which further confirms the reliableness of our classification. Details on the construction of the sample of fintech lenders are stated in the Online Appendix C1.

One thing to notice about our classification method is that we do not classify all non-banks as fintech lenders because one crucial feature of SBA lending programs is the participation of many traditional non-bank lenders, such as CRF Small Business Loan Company, LLC and Hana Small Business Lending, Inc., as means to facilitate the funding needs of less bank-connected small businesses. In the aspect of lending technology, these non-banks are similar to banks and are different from fintech companies. Other papers in small business lending (Gopal and Schnabl

[8] The first draw refers to the participation of the first-time borrowers in 2020 and 2021. The second draw is the second-time participation in 2021.

[9] Other papers studying the Paycheck Protection Program (Erel and Liebersohn (2020); Granja et. al. (2020); Li and Strahan (2020)) use the early release of the PPP data that contain borrower names only for loans *above* $150,000. The full release used in our paper contains borrower-level identifiable information for loans both above and below $150,000, which enables us to link with Yelp rating data for the full sample.

[10] To cross validate our consolidated fintech company list, we manually go through the entire sample of non-bank lenders and do not identify any lenders that are clearly a fintech company but not in our fintech lender list.

[11] The 2020-March data release includes both the originating and the servicing lenders and we classify the pair of lenders as a fintech lender when either of them is in our consolidated list of fintech lenders.

(2020)) and the mortgage credit market (Buchak et. al. (2018); Fuster et. al. (2019)) also make the distinction between fintech companies and other non-banks.

Along the process of identifying fintech lenders, we classify lenders into banks, Certified Community Development Financial Institutions (CDFIs) loan funds and Certified Development Companies (CDCs), and other non-banks. Using our definition of fintech lenders according to the SBA list, we include both non-bank and online-bank fintech lenders. We then match the PPP lenders in our final linked restaurant sample with financial institutions on the Federal Financial Institutions Examination Council (FFIEC) list[12]. Taking advantage of the lender information from FFIEC, we further determine whether the lender is a federally insured institution, credit union, and savings & loan association. Details on the lender classification and steps to match with FFIEC are in Online Appendix C2.

Secondly, we also need to identify minority-owned businesses among PPP loan recipients for a representative sample. One limitation of the PPP loan-level data is that the information on race and ethnicity of loan recipients is missing for almost 90% of the sample. As the application did not ask for demographic information on the business owners, the race and ethnicity information is self-reported by lenders and concentrated among a few lenders (Fairlie and Fossen (2021)). The coverage of the race and ethnicity information increases in later periods as the SBA began to pay more attention to the racial gap in the loan distribution.[13] Nevertheless, it is still possible that there is a selection bias in the sample that has the demographic information. Therefore, we do not rely on the demographic information in the original PPP loan-level dataset.

To address this challenge, we restrict to a sample of restaurants among the PPP recipients that we find a match on yelp.com and use the food type information on yelp.com as a proxy for the race and ethnicity information of the restaurant owners. We classify restaurants into four groups: Africans, Asians (including Pacific Islanders), Hispanics, and Whites. The detailed classification list is available upon request.[14] Our measure of minority-owned businesses is based on the assumption that the racial and ethnic group of the owner is highly and positively correlated with the food type of the restaurant. Admittedly, in reality, the two variables can be different. Therefore,

[12] We restrict to the lenders who lend more than 100 loans in the entire PPP program, excluding CDFI, CDC, and non-bank fintech lenders.

[13] The 2021-March release has an about 22% coverage rate of racial information. In comparison, the coverage rate is around 10% in the earlier release as reported in Fairlie and Fossen (2021).

[14] Some examples are African, Somali, and Soul Food as Africans; Asian Fusion, Japanese, Chinese, and Pakistani as Asians; Acai Bowls, Caribbean, and Mexican as Hispanics.

we cross validate our measure of minority-owned business by comparing the Yelp racial group variables and the PPP racial group variables. Appendix Table A3 reports the results. While we cannot rule out cases where we mismeasure the racial groups, overall, our race proxy based on Yelp information is highly and positively correlated with the true racial category and with a reasonable level of accuracy.[15]

The concurrent literature addresses this data incompleteness of demographic information by conducting zip-code/county level analysis (Erel and Liebersohn (2020); Fairlie and Fossen (2021)), restricting to the subset of the PPP recipients with demographic information (Atkins, Cook, and Seamans (2021)), estimating the racial group based on borrower name and location (Howell et. al. (2020)). One distinct paper is Chernenko and Scharfstein (2021) that links the PPP data with restaurant licenses and voter registrations in Florida and they identify the race and ethnicity group of restaurant owners using the registration information. As independent research, we also link the PPP data to other data sources to identify minority-owned businesses. Unlike Chernenko and Scharfstein (2021), our sample covers all the 50 states and D.C. across the U.S. The wide geographical scope of our sample and the fact that we do not rely on location information when building up the proxy allows us to investigate racial disparities across different locations as well as in the same location, which can provide a better understanding of the sources of racial disparities.

Thirdly, we use the customer ratings from yelp.com to gauge the double-differences in terms of the minority-non-minority gap between fintech and non-fintech borrowers. Yelp rating is used as a proxy for operational performance (Bernstein and Sheen (2016)) and shown to be related to revenue increase (Luca (2016)).[16] The feature that Yelp ratings have a uniform range from 0 to 5 provides a comparable way to investigate disparities in the valuation across lenders for borrowers of different racial groups. More specifically, we collect a full panel of the restaurant ratings so that we can study the restaurant operational performance for both the period before and during the

[15] Panel A of Appendix Table A3 shows that around 80.1%, 51.9%, and 89.6% of the African, Hispanic, and Asian restaurants based on the yelp information have an owner of the same racial group according to the PPP information, respectively. Panel B reports that around 61.5%, 16.2%, and 62.0% of the African Americans, Asians, and Hispanics own a restaurant of the corresponding type. The main false negatives come from the part of the African Americans owning a White type restaurant. Panel C reports the pairwise correlation between the PPP and yelp racial group measures, which shows strong and positive correlations, 0.35, 0.52, and 0.68 for Africans, Asians, and Hispanics respectively, and statistically significant at the 1% level.

[16] There is recent literature discussing the effectiveness of customer ratings (Mayzlin, Dover and Chevalier (2014)), and using the Yelp ratings as a measure of restaurant sales (Anderson and Magruder (2012)) and visits (Davis et. al. (2019)), and investigating the informativeness of customer ratings in residential home services (Farronato et. al. (2020)), physician choice (Xu, Armony and Ghose (2021)), and books on Amazon (Reimers and Waldfogel (2021)).

Covid-19 crisis. Using the full history of the ratings, we construct a restaurant-month panel of the Yelp ratings by taking the average and the total number of ratings in each month for each restaurant.

Lastly, we merge in other datasets to enrich the scope of our analysis, including other restaurant-level information from yelp.com, 7(a) and 504 program loan-level data during 1990-2019, and HUD USPS zip code crosswalk files. Details on variable definitions and data sources can be found in Table A1 in the Appendix.

3.2. Sample design

We construct a linked database by matching the borrowers in the PPP dataset to the restaurants on yelp.com. The PPP-Yelp linked dataset offers several advantages. First, it provides information on detailed borrower-level characteristics and a proxy for minority-owned businesses for a representative sample. Second, the eligibility criteria for the restaurant industry is that essentially all restaurants were eligible for PPP while the standard is higher in other industries. Details in the appendix. This rules out the possibility that our results are driven by sample selection bias due to eligibility.[17] Third, the restaurant industry is among the most Covid-19 vulnerable industries. Studying the restaurant borrowers can shed light on how Covid-19 sensitive industries perform during the crisis. Overall, we believe that our linked datasets give us a unique opportunity to study the small business loan market, especially for what drives minority borrowers to use fintech lenders.

We use both code-based algorithms and manual corrections for the matching procedure and employ strict matching criteria that only includes the matches between the PPP recipient and the yelp restaurant that have meaningful connections in terms of both the name and address. Details on the linking procedure are described in the Online Appendix C3. 104,293 loans are matched to a meaningful link on yelp.com, which account for 28.01% of the whole PPP sample in the *Food Services and Drinking Places* sector. The matching rate is reasonable given that our matching criteria are strict. For the empirical analysis, we focus on the period from April 2018 to March 2021 and limit the sample to restaurants that have at least one rating record since April 2018.[18]

[17] For example, if the eligibility is size-based, we would have a different sample of the minority-owned businesses than non-minority-owned businesses that are eligible for the PPP as the minority-owned businesses tend to be smaller.
[18] This deletes about 2.88% of the observations in the linked sample.

Online Appendix C3 also provides a comparison between the linked and unlinked sample which shows a high similarity between the linked and unlinked samples.

3.3. Summary statistics

We mainly use two datasets: one cross-sectional dataset that consolidates various data sources described above and one restaurant-level panel dataset on historical customer ratings. Our final cross-sectional dataset consists of 98,825 restaurant borrowers in the PPP that are active in business from April 2018 to March 2021[19]. The observation level is a restaurant-lender-loan triplet. The loan and lender characteristics are observed at the PPP loan origination time; the restaurant characteristics are from yelp.com and observed at the time of data collection (July and August in 2021). The restaurant-level panel dataset provides the monthly average of rating stars for the 98,825 restaurants in our sample from April 2018 to March 2021.

[INSERT TABLE 1 AROUND HERE]

Table 1.1 shows the summary statistics of key variables in the cross-sectional dataset for the borrowers in the 2020 (Panel A) and 2021 (Panel B) waves. We report the results for both the full and the matched samples. The matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, business type group (aggregated), food price range, and of a close employment size with a difference of at most five employees. By employing the matched sample methodology, we take into account the possibility that the above-described matching covariates may affect our results non-linearly.

The recipients in the 2021 wave appear to be different from the recipients in the 2020 wave in our sample. 32% of the 2020 and 38% of the 2021 recipients are minorities; 12% in 2020 and 6% in 2021 are in franchise chains; 9% in 2020 and 17% in 2021 use fintech lenders; 3% in 2020 and 2% in 2021 have lending relationships. The average borrower in 2020 (2021) has 18.62 (9.39) employees, waits 26.87 (41.12) days to gain an approved loan, and has a total number of 52.08 (33.01) customer reviews during the period from April 2018 to March 2021. Overall, the 2021 wave tends to contain a larger part of financially disadvantaged borrowers than the 2020 sample.

[19] We further exclude a total of less than 2% of the observations of non-restaurants, located in Puerto Rico, Northern Mariana Islands, Guam, and U.S. Virgin Islands, and where one yelp link is matched to multiple loans.

When comparing the full and matched samples, in 2020, the minority and racial group variables are close, with a slightly higher share of Asian-owned restaurants in the matched sample. In other dimensions, restaurants in the matched sample have fewer employees, less business capital, more days to gain an approved loan, are less likely to be franchised, more likely to use fintech lenders, similar in lending relationships, and are matched with lenders with a larger geographic lending scope. Similar patterns hold for the 2021 wave, except that approval days are slightly fewer for the matched sample in 2021. These differences in the full and matched samples are consistent with that the minority-owned businesses tend to be in a disadvantaged location and business status.

Table 1.2 shows the summary statistics of rating stars in the panel dataset for the borrowers in the 2020 (Panel A) and 2021 (Panel B) waves. The ratings are quite similar for the full and matched sample. However, the average rating is higher during the Covid-19 period (3.92 for the 2020 recipients and 4.06 for the 2021 recipients) than before the Covid-19 period (3.84 for the 2020 recipients and 3.95 for the 2021 recipients). These numbers also mean that the 2021 recipients have higher ratings than the 2020 recipients on average. The differences between the 2020 and 2021 recipients are worth noticing as the latter are more likely to be minority-owned, smaller but of higher ratings.

4. Existence of Racial Disparities in the Borrower-Lender Match

This section investigates whether there is a systematic difference in using fintech lenders versus traditional lenders in the PPP program for minority- and non-minority-owned restaurants. Moreover, motivated by the simple matching game model developed in section 2, we study how the customer ratings of the fintech and non-fintech loan borrowers differ between the minority- and non-minority-owned restaurants.

4.1. Fintech lenders in the PPP program

In this subsection, we present graphic illustrations of the usage of fintech and non-fintech lenders for minority- and non-minority-owned restaurants. Figure 3 shows the daily amount of loans in terms of million dollars processed by fintech lenders (panel (a)) and non-fintech lenders (panel (b)) for minority- and non-minority-owned restaurants. Major fintech lenders were allowed

to participate in the PPP program in 2020 only until one week after the initial launch.[20] Before the entry of major fintech lenders on April 10th, there is an enormous gap between the fraction of loans disbursed to the minority- and non-minority-owned businesses. For example, on the first day, the amount of loans disbursed to the minority-owned businesses is only 7.54% of the amount disbursed to the non-minority-owned businesses. While the minority-non-minority ratio of loan amounts narrows after the first four days, it remains at around 20% for traditional lenders. On the contrary, on the first day after the SBA's formal approval of fintech entry, fintech lenders processed more than three million dollars of loans for minority borrowers, which is about 35.96% of the amount fintech lenders disbursed to non-minority borrowers. The minority-non-minority ratio of loans delivered by fintech lenders is even higher for later days, which is above 50%.

In the second tranche, traditional lenders cover a relatively larger share of minority-owned businesses than in the first tranche, consistent with findings using the early data release of the subsample of larger loans (Fairlie and Fossen (2021)). Yet, overall, the gap between fintech and traditional lenders is still prominent, with a 53.38% minority-non-minority ratio for traditional lenders and a 75.27% minority-non-minority ratio for fintech lenders in terms of total loan amount delivered in the second tranche of the 2020 wave. A figure plotting the daily *number* of loans processed by fintech and traditional lenders for minority- and non-minority-owned businesses can be found in the Online Appendix A Figure A1, which shows a similar pattern.

[INSERT FIGURE 3 AROUND HERE]

We further decompose the minority-owned businesses into African-American-, Asian-, and Hispanic-owned businesses and plot the fintech and non-fintech daily disbursed loan amount in the Online Appendix A Figure A2. The patterns look analogical across the three racial groups, especially after the entry of major fintech lenders, suggesting that fintech lenders serve as a crucial channel of accessing PPP loan for all the three racial groups. We also plot the combination of the trends of the three racial groups in Online Appendix A Figure A3, which further confirms that the patterns are similar for different minority racial groups.

[20] https://www.lendacademy.com/fintech-lenders-can-finally-apply-to-be-part-of-the-ppp/. Some fintech lenders participated in SBA 7(a) programs before 2020, and therefore are allowed to process the PPP loans from the beginning. In our sample, the loans in the fintech lender category approved before April 10, 2020 are originated from Celtic Bank Corporation, Cross River Bank, Readycap Lending, L.L.C., and Sunrise Banks, National Association, and therefore are not the major fintech lenders in discussion such as Paypal and Kabbage.

4.2. Geographic variation in fintech lending

In this subsection, we explore the geographic variation in fintech lending in the PPP program. We start by looking at the minority and fintech loan shares in the PPP program independently. Figures 4(a) and 4(b) in the upper row plot the percentage of PPP loans, in terms of sum of loan amounts, disbursed to minority borrowers in each state in 2020 and 2021 respectively. The variation in the minority share across states is very limited in both years, which implies that comparing the geographic variation in minority shares per se might underestimate the minority-non-minority disparities in the PPP program.

[INSERT FIGURE 4 AROUND HERE]

Figures 4(c) and 4(d) in the lower row plot the geographic variation in the percentage of PPP loans delivered by fintech lenders across states in the 2020 and 2020 waves correspondingly. The fintech shares are similar across states in 2020, probably due to the much higher credit demand of borrowers of all types in 2020 than in 2021. The cross-state variation is more significant in 2021 and is more close to previous documented evidence (e.g., Buchak et al. (2018) for mortgage origination, Di Maggio and Yao (2021) for consumer loans, CBinsights (2021) for the amount of equity funding into fintech startups). For example, hometowns of earlier fintech lenders such as New York (19.02%) and California (22.25%) have higher fintech usage than surrounding states. Fintech lenders are also more popular in states where new top-funded fintech startups are located, such as Texas (25.43%) and Georgia (27.66%). One exception is Florida which has fintech share increasing from 11% in 2020 to 35% in 2021, probably because of the surge in COVID-19 cases. Similar plots using the total number of loans instead of the amount of loans are presented in Online Appendix A Figure A4.

Comparing the geographical variation in minority and fintech loan shares provides with additional clues on the difference in the racial disparity between fintech and non-fintech lenders. The variation in fintech shares does not coincide with the variation in minority shares, which suggests that fintech lenders are matched with minority versus non-minority borrowers in different magnitudes. There are potentially some underlying differences between the minority borrowers matched with fintech and non-fintech lenders, as we shall investigate in the regression analysis.

[INSERT FIGURE 5 AROUND HERE]

Figure 5 plots the state-level minority shares separately for fintech loans and non-fintech loans, which further confirms that fintech and non-fintech lenders play a different role in providing credit to minority-owned businesses. Figures 5(a) and 5(b) in the upper row plot the minority share for fintech loans, in 2020 and 2021 respectively. Figures 5(c) and 5(d) in the lower row plot the minority share for non-fintech loans, in 2020 and 2021 respectively. The cross-state variation in the minority shares for non-fintech loans (figures 5(c) and 5(d)) is similar to the cross-state variation in the overall minority shares (figures 4(a) and 4(b)). In contrast, we observe a larger dispersion across states in minority shares for fintech loans. These results suggest that fintech lenders are matched with a different segment of minority borrowers compared with non-fintech lenders. All patterns are similar when we use the total number of loans to measure minority shares, as shown in Online Appendix A Figure A5.

4.3. Fintech lenders and minority borrowers

Next, we investigate whether the minority-owned restaurants are more likely to use fintech lenders in the PPP program in a regression framework. We estimate the following specification:

$$I(Fintech)_{i,c} = \beta I(Minority)_i + \gamma X_i + \mu_c + \varepsilon_{i,c}$$

where the main dependent variable is a dummy variable equal to one if the restaurant owner *i* borrows from a fintech lender in the PPP program and 0 otherwise. The main independent variable is a dummy variable equal to one if the restaurant *i* is a minority-owned restaurant and 0 otherwise. The omitted category is non-minority-owned restaurants. In the specifications where we decompose the *Minority* dummy variable into the three major racial and ethnicity groups, the main independent variables, *African*, *Asian*, and *Hispanic*, dummy variables equal to one if the restaurant owner *i* is African Americans, Asians, and Hispanics correspondingly and 0 otherwise. The omitted category is other racial and ethnicity groups, mainly composed of White-Americans. To control for other borrower characteristics to the largest degree of data availability, we include *Employment* for business size, *I(Franchise)* for whether the business is under a franchise brand, *Business Type Dummies* for different company organizational format from corporation, L.L.C., to sole proprietorship, and self-employment (Details in Appendix-Table A1). We include city fixed

effects (μ_c) to control for variation in local economic exposure to the Covid-19 shock, such as cross-regional variation in COVID-19 cases, and pre-pandemic conditions that might affect the propensity to get a fintech loan.

[INSERT TABLE 2 AROUND HERE]

Panel A of Table 2 presents the results on the 2020 wave. Column (1) shows that being in the minority group is associated with a 4.78% higher likelihood of the borrower obtaining a fintech loan on average. In column (2), we compare the characteristics of business owners in the *same city* who borrow from different lenders by controlling for city fixed effects. The magnitude of the coefficient before the *Minority* Dummy decreases to 3.61%, implying that a main part of the difference in using fintech lenders between the minority and non-minority groups comes from the geographic variation across cities. Both results are statistically significant at the 1% level. In columns (3) and (4), we re-do the same analysis as in columns (1) and (2) but on the matched sample. Results on the *Minority Dummy* are robust for the matched sample, with similar economic magnitude and statistically significant at the 1% level.

Different racial and ethnicity groups may have different likelihood of fintech adoption. Columns (5) to (8) decompose the *Minority Dummy* into three dummies, *African*, *Asian*, and *Hispanic*, for the full sample and the matched sample, respectively. For African Americans and Asians, we still observe a prominent higher likelihood of using fintech lenders. Column (5) shows that African American- and Asian-owned restaurants are with an 8.00% and 7.43%, correspondingly, higher likelihood of using a fintech lender. However, for Hispanic borrowers, the difference in the likelihood of using fintech and traditional lenders is only 0.88%, which is small in terms of economic magnitude. Coefficients are statistically significant at the 1% level for all groups.

After controlling for city fixed effects in column (6), the coefficient before the *African* dummy decreases to 4.99%, which is around 37.63% of the coefficient without city fixed effects. The coefficient before the *Asian* dummy also decreases and becomes around 18.30% of the coefficient without city fixed effects. The coefficient before the *Hispanic* dummy becomes negligible and statistically insignificant when controlling for city fixed effects. Results are robust when using the matched sample which are presented in columns (7) and (8). The large reduction in the economic magnitude and statistical significant of the coefficients when controlling for city

fixed effects suggests that the geographic variation across cities explains a large degree in the usage of fintech lenders by minority-owned businesses.

Panel B of Table 2 presents the results on the 2021 wave. Similar as in the 2020 wave, we observe a higher likelihood of using fintech lenders for the minority-owned businesses, with the largest effect for African Americans, followed by Asians, and the smallest for Hispanics. The economic magnitude is even larger than as in the 2020 wave. For example, column (1) shows that the minority-owned businesses as a whole group is associated with an 8.24% higher likelihood of obtaining a fintech loan on average, almost amounts to twice as large as the coefficient in the 2020 wave. Similarly, in the specification shown in column (5) where we decompose the *Minority* dummy into *African*, *Asian*, and *Hispanic*, the coefficients are 2.02, 1.36, and 5.63 times as large as the coefficients in the 2020 wave respectively. The stronger effects in the 2021 wave can be the outcome of passing on the successful experience with fintech companies among borrowers in the minority communities and advertisements.

Cross-city variation plays an even larger role in the 2021 wave. As shown in column (2), the coefficient before the *Minority* dummy decreases by 1.65 times to 4.99% after controlling for city fixed effects. Similarly, as reported in column (6), the coefficient before the *Asian* dummy decreases to 6.10%; the coefficient before the *African* dummy becomes insignificant after controlling for city fixed effects; the coefficient before the *Hispanic* dummy decrease to 3.31% and becomes only statistically significant at the 10% level. These results suggest that the role of within-city variation in lender choices, potentially due to competition among borrowers, are reduced in the 2021 wave. Results are robust when using a matched sample which are presented in columns (3), (4), (7) and (8).

In all specifications, *Employment Size* is negatively related to the propensity to use fintech lenders, which is consistent with the existing papers showing that banks prioritize larger customers (Balyuk, Prabhala, and Puri (2020)). Interestingly, the coefficient before *Employment Size* is similar whether controlling for city fixed effects or not, implying that the cross-city variation in fintech usage are due to the difference in minority borrower shares, rather than the difference in borrower sizes. Franchised restaurants also tend to be less likely to apply the PPP loan through fintech lenders, which is as expected given that their parent companies have stronger relationship with banks than non-franchised restaurants.

Taken together, our evidence supports the argument that minority-owned businesses are more likely to substitute traditional lenders with fintech lenders. We find that this substitution effect is the strongest for African Americans, followed by Asians, and the smallest for Hispanics. To a large extent, the higher likelihood of using fintech lenders by minority-owned businesses is attributed to regional variation, which is consistent with the findings in the literature that disparities exist because minority-owned businesses tend to be located in areas with fewer bank branches (Erel and Liebersohn (2020); Wang and Zhang (2020)).

On the dark side, the regional variation tend to be attributed historically-rooted factors such as "bank deserts" on the lender side and language barrier and business capital on the borrower side and may not be alleviated in a short time period. As a result, we may still observe the difference in fintech usage between minority- and non-minority-owned businesses. On the bright side, the economic magnitude of the using likelihood of fintech lenders is larger in the 2021 wave than in the 2020 wave, consistent with a learning effect within the minority communities in order to access the government fund. The within-city variation also contributes in a smaller degree in the 2021 wave, suggesting an improvement in terms of equality in the loan distribution process in the 2021 wave compared with the 2020 wave.

4.4. Restaurant ratings

We next explore the existence of racial disparities through the lens of yelp customer ratings. Motivated by our matching game model, we investigate whether minority-owned restaurants are less undervalued with fintech lenders than with non-fintech lenders using the *Double-Difference* in ratings.

[INSERT TABLE 3 AROUND HERE]

Table 3 regresses the yelp ratings on the interaction term between the fintech lender indicator and the three minority racial group indicators respectively, which compares the minority-non-minority rating gap between fintech and non-fintech borrowers. Panel A presents the results for the 2020 wave, and Panel B for the 2021 wave. We look at the operational performance, proxied by customer ratings, separately for the periods before and during the Covid-19 crisis as restaurants may differ in their operational performance change due to the Covid-19 crisis, and thus may

experience different levels in seeking the PPP loan from traditional and fintech lenders. In each panel, columns (1)-(4) report the results for the before-Covid period, from April 2018 to March 2020, and columns (5)-(8) for the during-Covid period, from April 2020 to March 2021. Specifications mainly differ in terms of fixed effect controls and whether using the full or the matched sample. We account for within-restaurant correlation in errors by clustering all panel regressions by restaurants.

In the 2020 wave, for African-American-owned restaurants, Panel A columns (1)-(4) show that the coefficients before the interaction terms between the fintech lender indicator and the African-American indicator are insignificant when using ratings of the before-Covid period. However, as shown in columns (5)-(8), when using ratings of the during-Covid period, the coefficients before the interaction terms are negative and statistically significant at the level of 5%. For example, in column (5), the rating gap between African-American- and non-minority-owned restaurants is 0.25 star (or 6.5% of the sample mean) more negative for the borrowers of fintech lenders than for the traditional lenders. The difference in the results using the before- and during-Covid period suggests that the African-American-owned small businesses that are hit especially hard by the Covid-19 crisis (Fairlie (2020)) experienced relatively more difficulties in getting a PPP loan from traditional lenders.

For Asian-owned restaurants in the 2020 wave, we find a negative double-difference using both the before- and during-Covid period. For example, in column (1), the rating gap between Asian- and non-minority-owned restaurants is 0.08 star (or 2% of the sample mean) more negative for the borrowers of fintech lenders than for the traditional lenders. Results on the Hispanic-owned restaurants are insignificant. Results with and without city fixed effects are similar, suggesting that racial disparities exist both across- and within-cities. Results using the matched sample are robust.

We observe different results in the 2021 wave. The double-difference in ratings for the African-American- and Asian-owned restaurants become insignificant, yet for the Hispanic-owned restaurants, we observe a negative double-difference using ratings of the during-Covid period. For example, Panel B column (5) shows that the rating gap between Hispanic- and non-minority-owned restaurants is 0.18 star (or 4.6% of the sample mean) more negative for those who use fintech lenders than for those who use traditional lenders. Results using the matched sample are robust.

As we are looking at the first-time loan recipients instead of the re-applications in both the 2020 and 2021 waves, the differences in the double-difference in ratings among different racial groups imply a swift in the segment of borrowers covered by fintech lenders. One possible story can be that Africans and Asians are more open and are familiar with fintech lenders and start to use them in the 2020 wave. As most of the African and Asian borrowers in the blind zone of traditional lenders already participated in the PPP program in 2020, the additional part of the African and Asian borrowers in the 2021 wave via fintech lenders are similar to non-minority borrowers. Hispanics might be less aware of fintech lending before. However, through the massive media coverage of fintech in PPP, and probably through the stories of minorities, the part of Hispanic borrowers neglected by traditional lenders applied for the PPP loans via fintech lenders in 2021.

The coefficient on the fintech indicator is positive and statistically significant at the level of 1% in all specifications in the 2020 wave but becomes insignificant in the 2021 wave, which is consistent with our model's prediction that higher-rated borrowers self-select into fintech lenders. As the 2021 wave is a supplement to the 2020 wave, it is reasonable that the self-selection effect becomes much weak.[21]

In Online Appendix Table B3, we do the same analysis but employ one dummy variable, *Minority*, that equals one if the restaurant *i* is a minority-owned restaurant and 0 otherwise. Results are consistent with the findings presented here. Table B4 presents the results where we run regressions on separable subsamples of fintech and non-fintech borrowers. We find that in the 2020 wave, among the non-fintech borrowers, African-American-owned restaurants have a level of higher ratings. In contrast, among the fintech borrowers, we do not find a significant difference in ratings between African-American and non-minority-owned restaurants. In a similar vein, while Asian-owned restaurants have a lower level of ratings than non-minority-owned restaurants for both fintech and non-fintech borrowers, fintech borrowers have a more negative Asian-non-minority gap in ratings. In the 2020 wave, the Hispanic-non-minority gap in ratings is similar for those who borrow from fintech and those who from non-fintech lenders. But in the 2021 wave, the Hispanic-non-minority gap in ratings is more negative for fintech borrowers than for non-fintech

[21] The crowding-out effects of bank borrowers with lending relationships in our model is another explanation for the higher ratings of fintech loan borrowers. Without further information, we cannot empirically distinguish between the two explanations.

borrowers. Our findings are consistent with that traditional lenders have higher requirements for minority borrowers than non-minority borrowers, explicitly or through selection effects in matching.

Overall, we find that a smaller minority-non-minority rating gap for fintech users, suggesting that minority borrowers are less undervalued when matched with fintech lenders. Our evidence implies that non-minorities borrowers can access the traditional credit market relatively more easily. For minority borrowers with a similar rating level, they might have to turn to new technology-based lenders, such as fintech lenders.

4.5. Lender heterogeneity

We further explore heterogeneity among lenders by running the same regression specifications as in Table 3 but using a series of dummies, one for each lender. We focus on the biggest four fintech lenders: Cross River Bank, Kabbage, Square, and Paypal, and the largest seven banks: JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. We set the threshold so that each lender covers at least 1% of the observations in our restaurant-month panel dataset of ratings. In particular, Cross River Bank, JPMorgan, Bank of America, and Wells Fargo each covers about 2.20%, 4.74%, 6.96%, and 4.26% of the observations, and other lenders cover a share of 1%-2% of the observations per lender.

[INSERT FIGURE 6 AROUND HERE]

Figure 6 provides the graphic illustration for the largest minority group in our sample -- the Asian-owned restaurants. Consistent with the pooled-lender regression results, compared with non-fintech lenders, the Asian-non-minority gaps in ratings are negative for the 2020 wave for all the fintech lenders, except for that the rating gap is slightly positive Cross River Bank using ratings during the Covid-19 period. Results for banks are mixed. For the largest three banks, JPMorgan, Bank of America, and Wells Fargo, the rating gap is either small or not significantly different from zero, suggesting that big banks provide credits to a similar group of minority- and non-minority-owned restaurants in terms of rating levels. For relative “small” big banks, the rating gap is positive.

In 2021, there is no clear difference between fintech lenders and banks. This is in alignment with our pooled-lender regressions and implies an improvement in 2021 that fintech and non-

fintech lenders provide credit to a similar segment of minority- and non-minority-owned businesses. This change in 2021 can be the result of lenders' reaction to the media pressure in reducing racial discrimination. It can also be attributed to the less demanding credit needs of borrowers so that the constraints for minority borrowers are relaxed.

Online Appendix Figure A7 and Figure A6 present similar plots for the Africans and Hispanics respectively where the patterns are consistent with results in pooled-lender regressions.

5. Sources of Racial Disparities

In this section, we investigate the sources of frictions that can contribute to racial disparities in fintech usage and the rating gap between fintech and non-fintech borrowers. The first piece of key insights from our matching game model is that a higher likelihood of fintech usages among minority-owned restaurants than among non-minority-owned restaurants may not directly speak to underlying racial disparities because it can result from many factors.

Firstly, a higher fintech usage among minority-owned restaurants can be explained by a combination of the self-selection effect of higher-rated restaurants and a higher average rating of minority-owned businesses. This case is more accidental and is not related much to the racial discrimination in the small business lending market. In addition, our empirical results from the previous section also provide little supports to it. We do observe a positive correlation between fintech usage and rating levels for the recipients in the 2020 wave, although the correlation becomes insignificant and negative for the recipients in the 2021 wave. However, for Asian and Hispanic restaurants, the rating levels are lower on average and therefore are not consistent with the prediction of higher usage of fintech lenders. African-American restaurants in the 2020 wave have a higher rating level on average in the pre-Covid period, but the rating difference becomes insignificant during the Covid-19 pandemic.

Overall, there is no systematic evidence supporting this self-selection explanation for the higher likelihood of fintech usage among minority-owned restaurants. In a similar vein, the combination of the crowding-out effect of borrowers with lending relationships and a higher average rating of minority-owned businesses has little empirical support at least in our sample.

Secondly, and more interestingly is that a smaller share of minority-owned restaurants have lending relationships, and therefore the minority-owned restaurants are relatively more affected by

the crowding-out effects of restaurants with lending relationships. This explanation speaks to one source of frictions in the small business lending market that comes from racial inequality in lending relationships. Therefore, in section 5.1, we test this hypothesis by comparing the share of borrowers with lending relationships for the minority- and non-minority-owned restaurants.

The second piece of key insights from our model, which is perhaps more important, is that the racial bias in the valuation of the borrower-lender matches of different types leads to a fintech-minority double difference in rating levels. In the previous section, we provide empirical evidence on the existence of such a double difference. In this section, we further explore what contributes to the existence of racial disparities. The source of the frictions can lie in the user-friendliness of different types of lenders, favoritism due to lending relationships, as well as financial institution coverage.

Our model predicts that a larger difference in the tech-savviness between the minority and non-minority borrowers means a larger racial disparity in the fintech-minority double difference in rating levels. Similarly, the racial disparity is also positively related to the difference in the value of lending relationships between the minority and non-minority borrowers. As there is no good measure of tech-savviness or value of lending relationship, we cannot directly test these predictions. Instead, we use some factors that affect the tech-savviness gap or the lending-relationship-value gap between minority and non-minority borrowers as a way to indirectly test these predictions. Moreover, investigating these factors speaks directly to the sources of frictions that lead to the racial disparity in the small business lending market.

In particular, in section 5.2, we study whether the business capital of borrowers can alleviate the racial disparities, and in section 5.3, we study whether a larger relative geographic lending scope of lenders and thus less attention allocated to each region, may aggravate the racial disparity.

5.1. Minority borrowers and previous lending relationships

[INSERT TABLE 4 AROUND HERE]

Table 4 reports the results on the lending relationships for the matched sample for the 2020 (Panel A) and 2021 (Panel B) waves. In the 2020 wave, the minority recipients, compared with non-minority recipients, are less likely to have previous lending relationships and have less

intensive lending relationships. More specifically, column (1) shows that after controlling for other business characteristics, Asian (Hispanic)-owned restaurants are 0.72% (1.11%) less likely to have lending relationships, amounting to 24% (37%) of the sample mean, where lending relationships are proxied by a dummy variable that equals one if the borrower has at least one SBA 7(a) or 504 loans during the period of 2009-2019. In column (2), we further control for city fixed-effects, and the likelihood difference enlarges to 1.00% for Asian-owned restaurants but narrows to 1.03% for Hispanic-owned restaurants. The changes in the likelihood difference due to city fixed effects imply that Asian-owned restaurants tend to be located in areas with less financial access within the city. On the other hand, the racial disparities for Hispanic-owned restaurants, to a larger degree, come from the variation in cities where they do the businesses. Coefficients before the Asian and Hispanic dummies are statistically significant at a level of 1% for all specifications. Coefficients before the African American dummy are insignificant but still negative.

Columns (3) and (4) (columns (5) and (6)) use the number (USD amount) of the previous SBA 7(a) and 504 loans the borrower had in 2009-2019 to measure the intensity of the lending relationships. Results are similar as in specification using the dummy variable of lending relationships. Coefficients before the racial groups become insignificant in most specifications in the 2021 wave. Results for the full sample are reported in Online Appendix Table B5 and are robust.

5.2. Business capital of borrowers

Minority-owned restaurants tend to have a business model that is more informal and less familiar to outsiders. To alleviate the issue, business capital can be a way to provide more information about the restaurant. Moreover, it can be a type of soft asset that serve as a role of collateral. Therefore, the business capital of borrowers may mitigate the racial disparities in the small business lending market.

We use the total number of ratings during our entire analysis sample period from April 2018 to March 2021 as a proxy for business capital.[22] For two otherwise same restaurants, the one with more reviews has more available information and can be seen as having a better reputation.

[22] Shi (2021) uses the firm size as a proxy for business capital and study how business capital increases the likelihood of being PPP recipients.

[INSERT TABLE 5 AROUND HERE]

Table 5 reports the results on the role of business capital for the matched sample. Consistent with our model's prediction that restaurants with a higher level of business capital are associated with a lower level of racial discrimination, the coefficients before the triple interaction among the fintech lender indicator, the minority borrower indicator, and business capital are positive and significant at the 1% level in all specifications for Asian- and Hispanic-owned restaurants in the 2020 wave.

For example, column (1) shows that using ratings in the before-Covid period and controlling for other business characteristics and month fixed effects, an increase of 100 reviews during our entire analysis sample period, which amounts to around one unit of sample deviation, is associated with a 0.11 star (or 1.38 times of the original racial gap) smaller fintech-minority rating gap for the Asian recipients in the 2020 wave. Column (2) controls for city-month fixed effects and results are similar. In columns (3) and (4), we measure the racial gap using ratings in the during-Covid period and results are robust.

Columns (5) to (8) present the results for the 2021 wave where we observe coefficients of almost twice larger of the coefficients in the 2020 wave for Asian-owned restaurants. Coefficients before the triple interaction terms with Hispanic-owned restaurants become insignificant. In both the 2020 and 2021 waves, the coefficients before the triple interaction terms with African-American-owned restaurants are insignificant. Results on the full sample are reported in the Online Appendix Table B6 and are robust.

5.3. Geographic scope of lenders

Lending relationships may have a lower value for minority-owned than non-minority-owned businesses due to discrimination. This can be exaggerated by less attention and resources from the lenders that are allocated to the region where the borrower is located as the value of lending relationships tend to be formed and reinforced through interactions.

We use the relative geographic lending scope (GS_r) as a proxy for the relative attention and resources allocated to the region by the lenders. GS_r is calculated as the total number of zip codes divided by the total number of cities that the lender covers in the entire PPP loan sample. For this part of the analysis, we drop CDFIs/CDCs as they may have specific regional requirements.

[INSERT TABLE 6 AROUND HERE]

Table 6 reports the results on the impact of relative geographic lending scope (GS_r) for the matched sample. Consistent with the prediction of our model that restaurants matched with a lender of a smaller GS_r are associated with a lower level of racial discrimination, the coefficients before the triple interaction among the fintech lender indicator, the minority borrower indicator, and GS_r are negative whenever the coefficients are significant at a level of at 5%.

In alignment with our baseline results in Table 3, the coefficients are significant for African-American-owned restaurants in the 2020 wave using during-Covid period ratings, for Asian-owned restaurants in the 2020 wave using both before- and during-Covid period ratings, and for Hispanic-owned restaurants in the 2021 wave using during-Covid period ratings. For example, column (1) shows that using ratings in the before-Covid period and controlling for other business characteristics and month fixed effects, an increase of one location in GS_r is associated with a 0.06 star (or 0.75 times of the original racial gap) larger fintech-minority rating gap for the Asian recipients in the 2020 wave. Results with and without city-month fixed effects are similar. In addition, results on the full sample are reported in the Online Appendix Table B7 and are robust.

To further demonstrate that it is the *relative* geographic lending scope that affects the racial disparities, we re-do the analysis by including both the geographic lending scope at the city level (GS_{city}) and the geographic lending scope at the zip-code level (GS_{zip}). Results are presented in Online Appendix Table B8. Consistent with the results using the relative geographic lending scope (GS_r), the coefficients are positive for the triple interaction with GS_{city} and negative for the triple interaction with GS_{zip} for the pairs that are significant at a level of at least 5%. The positive sign for the triple interaction with GS_{city} suggests that a larger geographic coverage of fintech lenders can be means to reduce racial disparities.

6. Alternative Explanations

6.1. Other lender types

In this section, we discuss several non-technology-related features of fintech lenders that might coincidentally lead to our main empirical findings of the rating gap. Since we do not have systematic data on lender features, we use various lender type variables to investigate the impact

of those features on the borrower-lender matching outcomes. In particular, we study the possible effects of being new entrants, a different customer base, a different lending philosophy such as community development orientation, non-federally-insured, and non-traditional funding source.

6.1.1. First-time bank participants

[INSERT TABLE 7 AROUND HERE]

Firstly, it might be that fintech lenders attract a different segment of borrowers because they are new entrants to SBA programs. We test this hypothesis by studying the first-time bank participants. There are 672 out of 4,131 PPP banks that are also new participants for SBA programs and they account for around 4.04% of the loans. However, Table 7 shows that the relationship between minority borrowers and the likelihood of being matched with newly entered banks is significantly lower for Asian-owned restaurants and insignificant for African-American- and Hispanic-owned restaurants.

[INSERT TABLE 8 AROUND HERE]

Moreover, Table 8 shows that the fintech-minority double-difference is insignificant for all racial groups in 2020 and positive in 2021 for African-American- and Asian-owned restaurants. Our results indicate that, unlike fintech lenders, first-time banks attract a segment of higher-rated minority-owned restaurants than non-minority-owned restaurants if anything. This does not support the hypothesis that fintech lenders extend the credit access to a segment of more undervalued minority borrowers because they are new entrants to SBA programs.

6.1.2. Credit unions

Secondly, fintech lenders tend to have better loan terms than banks in normal time which might develop a different customer base for them. When borrowing the PPP loans, customers who are more familiar with one particular type of lenders naturally come to that type of lenders. We test this hypothesis by studying another type of bank alternatives: credit unions. If it is the unobserved characteristics of borrowers who find better loan terms more attractive, instead of

racial discrimination, that lead to the minority-non-minority gap we document, we should observe a similar pattern for the comparison between credit unions and banks and between fintech lenders and banks.

[INSERT TABLE 9 AROUND HERE]

Credit unions are an important part of PPP lenders. 409 out of the 3,658 lenders that we find a match with FFEIC are credit unions, accounting for 3.48% of the loans. Results on the comparison between credit unions and banks are mixed. Table 9 shows that Asian-owned restaurants are less likely to use credit unions, which is the opposite of the results of fintech lenders. Similar to fintech usage, African-American- and Hispanic-owned restaurants are more likely to use credit unions.

[INSERT TABLE 10 AROUND HERE]

However, Table 10 reports a negative double-difference in the rating levels for Asian-owned restaurants and a positive double-difference in the rating gap for African-American-owned restaurants when the coefficients are statistically significant at least at the 5% level. The same signs of the coefficients of the likelihood of fintech usages and the double difference in the rating levels suggest that the part of minority borrowers served by credit unions are those who have a better evaluation in the traditional credit market, rather than those who are more undervalued in the traditional credit market. That said, we do not find the same results for credit unions as for fintech lenders.

6.1.3. Community Development Financial Institutions/Corporations

Thirdly, we investigate whether fintech lenders mimic the role of community development financial institutions (CDFIs) and community development corporations (CDCs). There are 54 CDFIs/CDCs in the sample of 4,185 lenders, accounting for 0.72% of the loans. We exclude fintech lenders and other non-banks to make a clean comparison.

[INSERT TABLE 11 AROUND HERE]

At the first glance, CDFIs and CDCs play a similar role as fintech lenders. Table 11 shows that minority-owned restaurants of all racial groups are more likely to use CDFIs/CDCs in the 2020 wave. However, Results become insignificant and even significantly negative for Asian-owned restaurants in the 2021 wave.

[INSERT TABLE 12 AROUND HERE]

Moreover, in Table 12 we find no significant results on the double-difference in the rating levels, except for Asians in the 2020 wave using the before-Covid ratings. Our findings imply that while CDFIs and CDCs are able to cover more minority-owned businesses, they play a limited supplemental role in extending credits to minority-owned businesses that are more undervalued by traditional lenders.

6.1.4. Federally-insured lenders and Savings & Loan Association

In addition, Online Appendix presents results on two other potential features of fintech lenders that might lead to our racial disparity results. Firstly, our racial disparity results might be driven by the regulation difference in federally-insured and non-federally-insured lenders.[23] For example, minority borrowers might gain the PPP information later and applied later when more non-insured lenders participated. We investigate the feature of non-federally-insured (Table B9 and Table B10) by comparing the 11 non-federally-insured lenders with other federally-insured lenders. Secondly, we test on the non-traditional funding source feature (Table B11 and Table B12) by using Savings & Loan Associations (S&Ls) who mainly offer affordable mortgages as a comparison group to banks. There are 25 S&Ls and account for 0.16% of the loans in our sample.

Our results do not support that the non-federally-insured or non-traditional funding source can explain the findings on the double-difference in the rating levels for fintech lenders. While we find that Asian-owned restaurants are more likely to use non-federally insured lenders, we do not find significant results on the double-difference in the rating levels. African-American- and Hispanic-owned restaurants are even shown to be less likely to use non-federally insured lenders

[23] The PPP Lender Information Sheet states that all federally insured depository institutions, federally insured credit unions, and Farm Credit System institutions are eligible to participate in this program. For non-insured lenders, as most fintech lenders are, they need to apply for approval to be enrolled in the program.
https://home.treasury.gov/system/files/136/PPP%20Lender%20Information%20Fact%20Sheet.pdf

or have a positive double-difference in the rating levels. Likewise, we find that minority-owned restaurants are less likely to use S&Ls and have a positive double-difference in the rating levels for S&Ls if anything.

To recap, in this section, we show that for other types of lenders, there is no consistent evidence that supports our model's prediction on the negative double-difference in the rating levels. Unlike fintech lenders, we do not find evidence that new bank participants, credit unions, CDFIs/CDCs, non-federally-insured lenders, and S&Ls are likely to provide credit accesses to the segment of minority borrowers that are more undervalued in the traditional market.

6.2. Loan approval speed

Another alternative explanation of our racial disparity results is a difference among borrowers in the preference of loan processing speed that coincides with using fintech lenders. Online Appendix Table B13 shows that on average fintech lenders have a higher loan processing capacity. In addition, the existing literature documents that fintech lenders process mortgage applications much faster than other lenders (Fuster et. al. (2019)). Therefore, it might be that a different group of minority and non-minority borrowers prefer quicker loan processing more and turn to fintech lenders disproportionally.

[INSERT TABLE 13 AROUND HERE]

Table 13 shows the regression results that compare the difference in the number of days needed to get the loan approved from the beginning of each PPP wave between the minority and non-minority borrowers matched with fintech and non-fintech lenders.[24] In the 2020 wave, the double-difference in approval days is insignificant for the African-American- and Hispanic-owned restaurants. For Asian-owned restaurants, results are positive and significant at the 1% level. For example, column (1) reports that the Asian-non-minority gap in approval days is 2.23 days longer for the fintech borrowers than for non-fintech borrowers. Results are robust across specifications,

[24] The measure based on approval dates is not the exact loan processing speed of the lenders. However, we do not have information on the application dates, and the measure using approval dates provides information on borrowers' preference for loan processing speed given that all the loan application starting dates are the same for all lenders.

as shown in other columns. This indicates that minority borrowers who turn to fintech lenders are more patient than their non-minority counterparts, consistent with a higher barrier they face to access to the traditional credit market.

In the 2021 wave, coefficients before the interaction terms between the racial group and fintech indicators become negative for Asian- (8.11 days shorter) and Hispanic-owned restaurants (8.72 days shorter). Results on African-owned restaurants are insignificant. The results might because that fintech lenders further improve their loan processing speed in 2021, given fintech platforms are more adaptive for a similar lending task in the second year. It could also be that or the group of minority borrowers supplemented by the 2021 wave is no longer those who are overlooked by the traditional credit market.

In a robustness check reported in Online Appendix Table B14, we address the issue that fintech lenders are not allowed to participate at the beginning of the 2020 wave. We limit the sample period to 1) after the official approval date of fintech entry, and 2) the second tranche. Results are robust and even stronger when limiting to the second tranche.

[INSERT TABLE 14 AROUND HERE]

Table 14 reports results on the robustness check of Table 3 where we control for the approval date fixed effects. This gives the estimation of the double difference in rating levels for loans approved on the same day, and thus rules out differences attributed to the borrower's position in the PPP application queue. Coefficients before the interaction terms between the racial group and fintech indicators are very close to those reported in Table 3. This implies that the racial disparities that we demonstrate do *not* come from a difference in loans approved earlier or later.

Overall, our findings suggest that minority borrowers turned to fintech lenders in the PPP program *not* because they have a higher preference for getting the loan earlier. In fact, our results show that minority borrowers who applied for a loan through fintech lenders have a longer waiting time on average to have an approved loan.

7. Conclusion

This paper studies whether fintech lenders can expand the scope of minority-owned small businesses in the credit market. We use the PPP program as a laboratory to study the question

because it has the advantages of a high likelihood of participation of minority borrowers who might be "hidden" in the loan dataset in normal time. Moreover, many cofounding factors are largely controlled for by the regulation or the Covid-19 crisis, such as loan term, application starting date, and credit demand. Using information from yelp.com, we construct a panel of customer ratings as a proxy for operational performance and develop a proxy of minority-owned businesses using the food type information.

Consistent with the existing literature, we find that minority-owned businesses are more likely to use fintech lenders. In a simple two-sided matching game model, we show that this phenomenon can be attributed to both ex-ante differences in the customer rating distribution and tech-savviness of the restaurant borrowers and an ex-post gap in the valuation of the borrower-lender matches. To further distinguish the two channels, we need to estimate the double-differences in ratings between the minority-non-minority borrowers when matched with fintech and non-fintech lenders. Empirically, we document that the difference between minority- and non-minority-owned restaurants in customer ratings is smaller for fintech lenders compared with non-fintech lenders, which suggests that minority-owned restaurants are less undervalued when matched with fintech than with non-fintech lenders. We do not find a similar pattern for first-time banks, community development financial institutions, or credit unions. The language barrier, business capital, and lending relationship contribute to the difference between minority- and non-minority-owned small businesses.

This paper studies the first large-scale government loan program where major fintech lending platforms, such as Paypal, Kabbage, and Funding Circle, are allowed to be eligible lenders. Our study has important policy implications that speak to the debate on whether to allow for the participation of fintech lenders in fully or partially guaranteed government loan programs. Our findings suggest that there are systematic biases and blind spots in the traditional loan distribution channel and that can be covered by fintech lenders. This has implications beyond the Covid-19 period. Whether the credit access provided by fintech lenders improves the financial and operational performance of those underserved borrowers is an interesting topic for future research. Moreover, the impact of introducing fintech lenders to the lending market on traditional lenders is also a promising avenue for future research.

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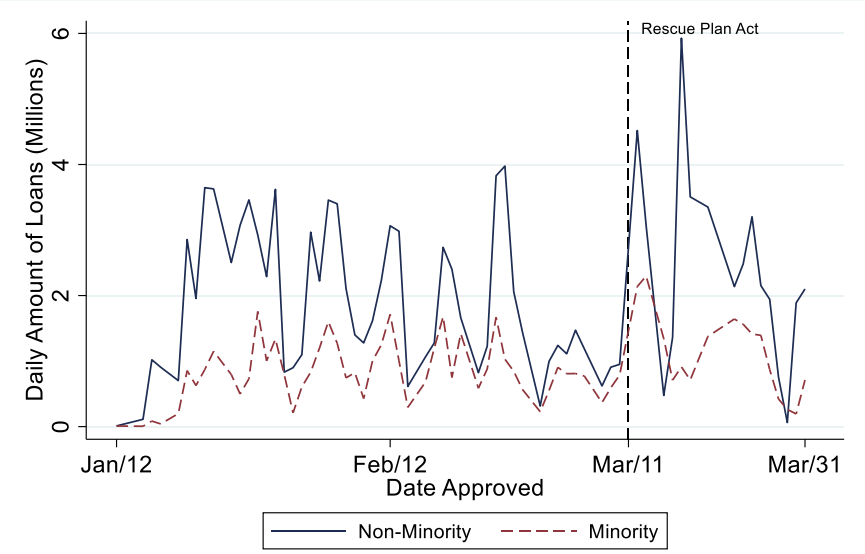
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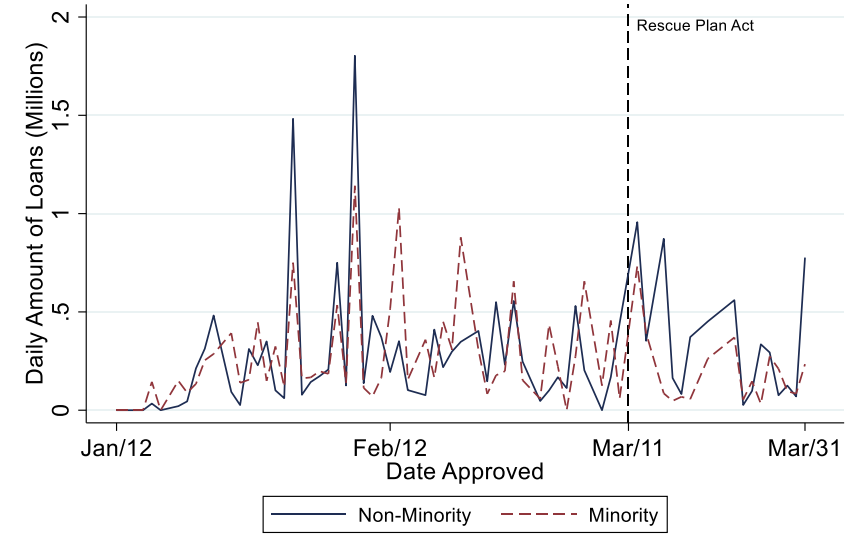
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Figures



(a) 2021 PPP, Non-Fintech Lenders



(b) 2021 PPP, Fintech Lenders

Figure 1: Minority- and Non-Minority-owned Businesses in the 2021 PPP Fintech vs. Non-Fintech

This figure plots the daily amount of PPP loans processed by non-fintech (panel (a)) and fintech (panel (b) lenders that are received by minority- and non-minority-owned restaurants in the 2021 PPP wave for our sample of analysis. The 2021 wave spans the period from January 12, 2021 to March 31, 2021. The y-axis stands for the daily amount of loans processed, in the unit of USD millions, and the x-axis stands for the loan approval date. The blue solid line plots non-minority-owned restaurants and the red dashed line plots minority-owned restaurants. The vertical dashed line indicates the time of the American Rescue Plan Act of 2021 that is enacted on March 11, 2021.

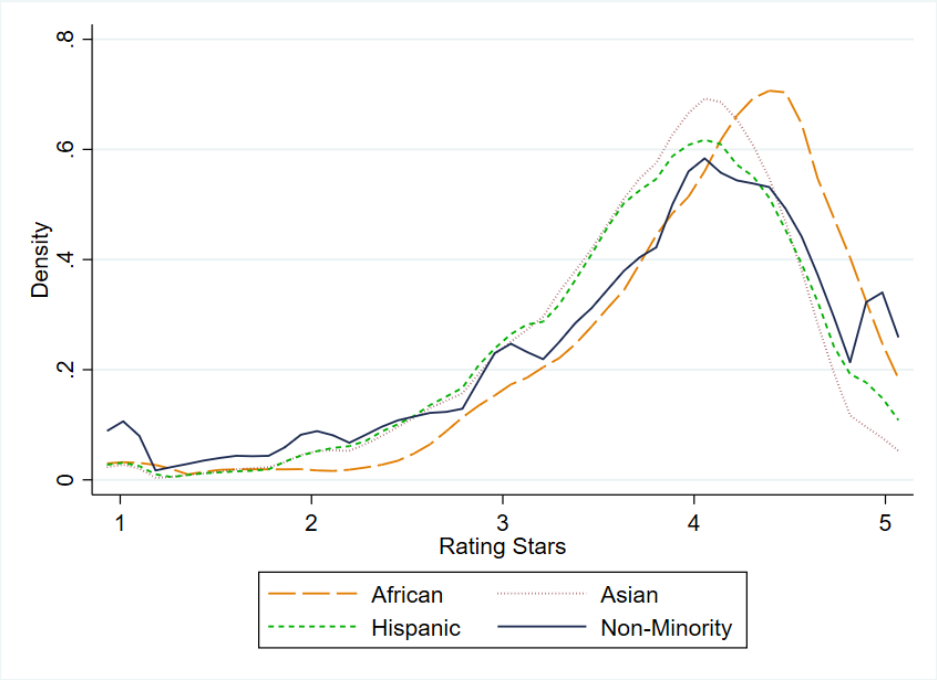
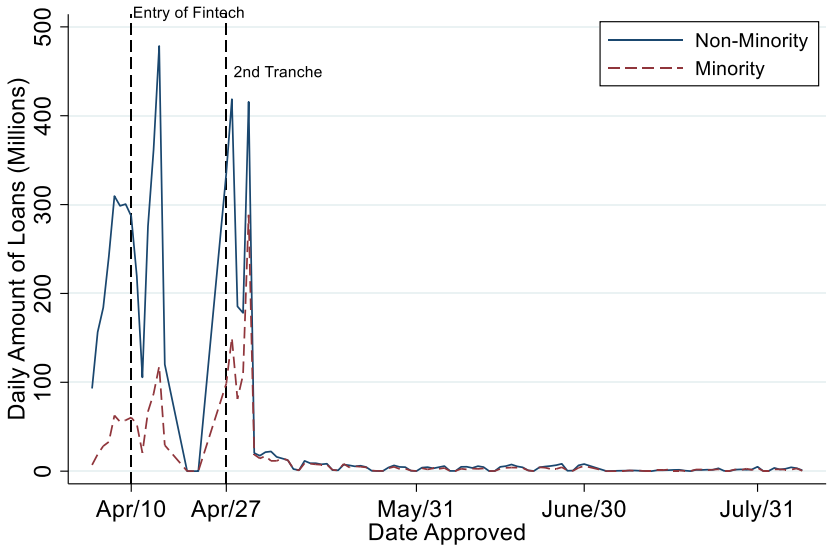
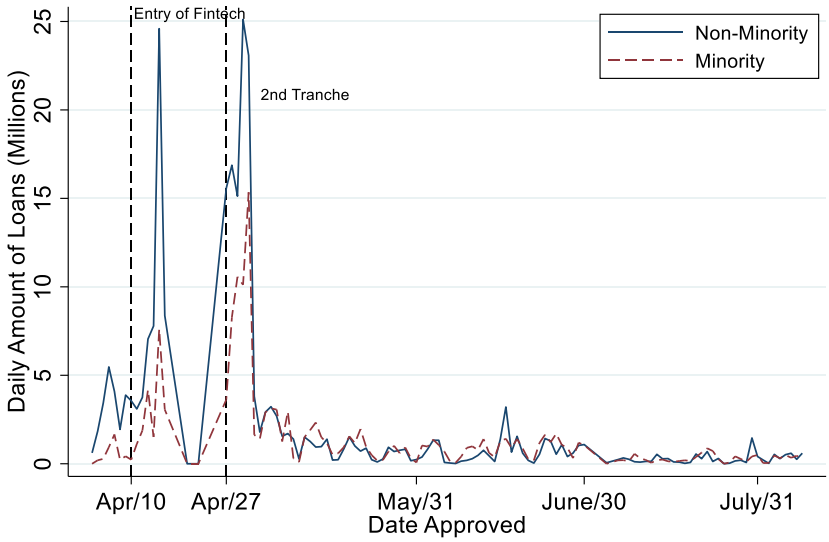


Figure 2: Distribution of Restaurant Ratings across Borrower Racial Groups

This figure plots the density of restaurant ratings for each racial group. Data is the customer rating stars from yelp.com. We calculate the mean of the monthly average of ratings from April 2018 to March 2021 for our linked sample of restaurants used in the main analysis.



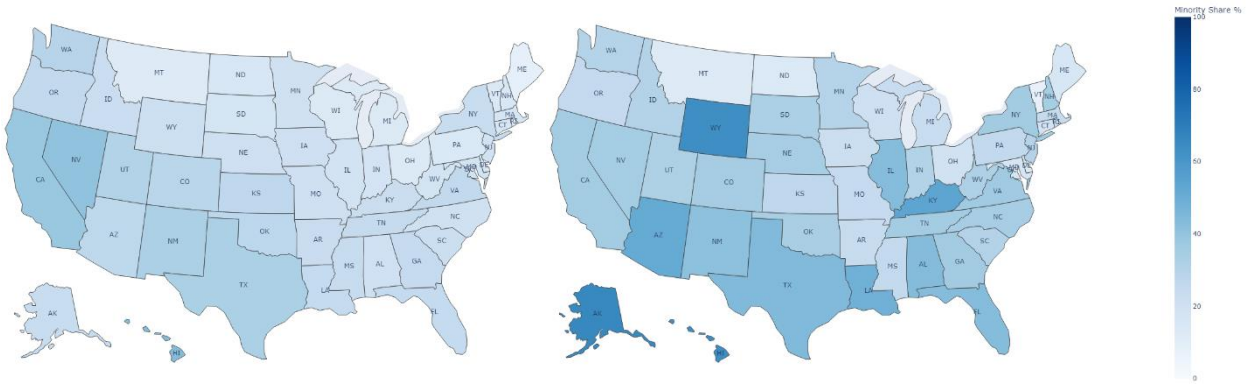
(a) 2020 PPP, Non-Fintech Lenders



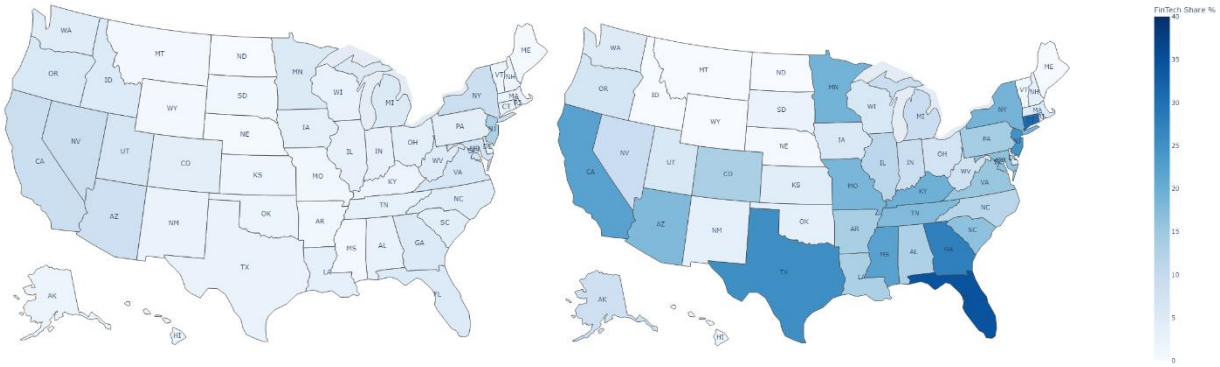
(b) 2020 PPP, Fintech Lenders

Figure 3: Minority- and Non-Minority-owned Businesses in the 2020 PPP Fintech vs. Non-Fintech

This figure plots the daily amount of PPP loans processed by non-fintech (panel (a)) and fintech (panel (b)) lenders that are received by minority- and non-minority-owned restaurants in the 2020 PPP wave for our sample of analysis. The 2020 wave spans the period from April 3, 2020 to August 8, 2020. The y-axis stands for the daily amount of loans processed, in the unit of USD millions, and the x-axis stands for the loan approval date. The blue solid line plots the non-minority-owned restaurants and the red dashed line plots the minority-owned restaurants. The first vertical dashed line indicates the time of the entry of fintech lenders on April 10, 2020 and the second vertical dashed line indicates the time of the beginning of the second tranche of the 2020 PPP on April 27.



(a) Minority Share in the 2020 PPP (b) Minority Share in the 2021 PPP

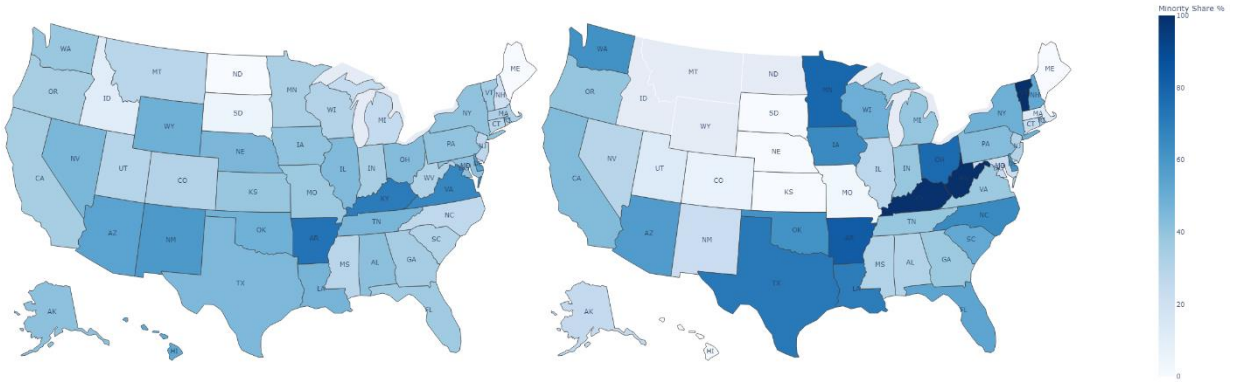


(c) Fintech Share in the 2020 PPP (d) Fintech Share in the 2021 PPP

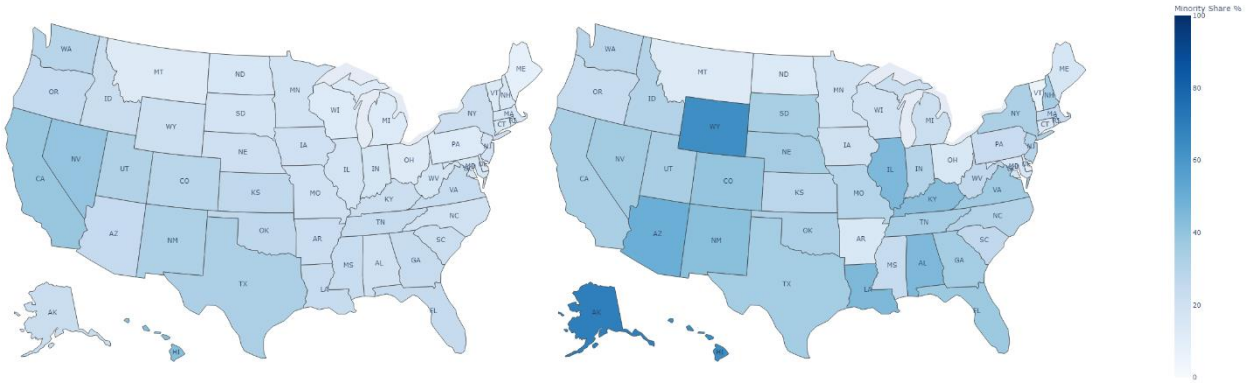
Figure 4: Percentage of Loans Distributed (Amount)

Minority-owned and Fintech

This figure plots the share of loan amounts (USD) distributed to minority-owned restaurants in the 2020 (panel (a)) and in the 2021 (panel (b)) waves, and the share of loan amounts (USD) processed by fintech lenders in the 2020 (panel (c)) and the 2021 (panel (d)) waves, based on our sample of analysis. The *Minority Shares* range from 0% (the lightest blue) to 100% (the darkest blue).The *FinTech Shares* range from 0% (the lightest blue) to 40% (the darkest blue).



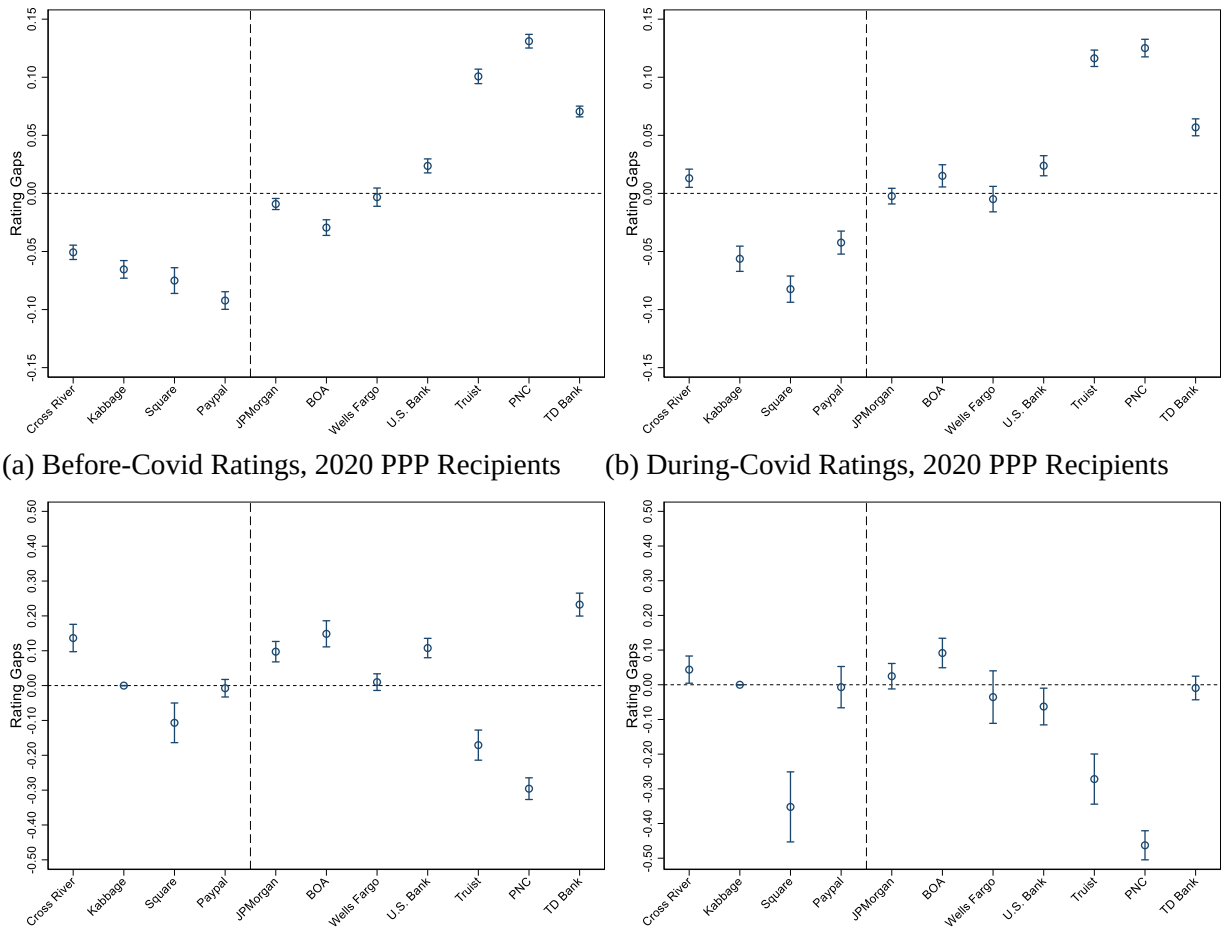
(a) Minority Share (Fintech) in the 2020 PPP (b) Minority Share (Fintech) in the 2021 PPP



(c) Minority Share (Non-Fintech) in the 2020 PPP (d) Minority Share (Non-Fintech) in the 2021 PPP

Figure 5: Percentage of Loans Distributed to Minority-owned Businesses Fintech vs. Non-Fintech (Amount)

This figure plots the share of loan amounts (USD) distributed to minority-owned businesses processed by fintech (panel (a) and (b)) and non-fintech (panel (c) and (d)) lenders in the 2020 and 2021 waves, based on our sample of analysis. The *Minority Shares* range from 0% (the lightest blue) to 100% (the darkest blue).



(a) Before-Covid Ratings, 2020 PPP Recipients (b) During-Covid Ratings, 2020 PPP Recipients

(c) Before-Covid Ratings, 2021 PPP Recipients (d) During-Covid Ratings, 2021 PPP Recipients

Figure 6: Minority-Non-Minority Rating Gap (Asian-owned)
Fintech vs. Non-Fintech

This figure plots the minority-non-minority rating gap for Asian-owned restaurants in the 2020 wave using historical ratings before the Covid-19 crisis (panel (a)) and during the Covid-19 crisis (panel (b)), and for Asian-owned restaurants in the 2021 wave using the before-Covid ratings (panel (c)) and during-Covid ratings (panel (d)). The y-axis stands for the coefficients before the interaction terms between the racial group indicator and lender indicators of the regression specifications as the same as in Table 3, except that we decompose the fintech indicator into a series of dummies for each big fintech lender and bank. The x-axis stands for the lenders. We focus on the biggest four fintech lenders in our sample: Cross River Bank, Kabbage, Square, and Paypal, and the largest seven banks in our sample: JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. In each regression, the dependent variable is the *Rating Stars*, within the range of 0 to 5, based on the customer ratings from yelp.com. The *Asian* indicator is defined to be 1 for restaurants with the corresponding cooking style. The $Lender_j$ (*e,g., Kabbage*) indicator is defined to be 1 for loans backed by that lender (e.g. by Kabbage). The omitted category is all other lenders. Control variables are the same as in Table 3 which contain lender dummies, racial group dummy, employment size, franchise dummy, month-city fixed effects, business type fixed effects, and eating policy dummies. Standard errors are clustered at the restaurant-lender level.

Table 1 Summary Statistics

Table 1.1 Restaurant and Lender Characteristics – Cross Section

	Panel A: 2020 PPP First Draw															
	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
I(Minority)	92,557	0.32	0.46	0	0	0	1	1	86,097	0.33	0.47	0	0	0	1	1
I(African Ame.)		0.01	0.08	0	0	0	0	1		0.01	0.08	0	0	0	0	1
I(Asian)		0.18	0.39	0	0	0	0	1		0.20	0.40	0	0	0	0	1
I(Hispanic)		0.13	0.33	0	0	0	0	1		0.13	0.34	0	0	0	0	1
Employment		18.62	31.02	1	5	11	21	500		14.79	17.44	1	5	10	19	500
I(Franchise)		0.12	0.33	0	0	0	0	1		0.11	0.32	0	0	0	0	1
I(Fintech)		0.09	0.29	0	0	0	0	1		0.10	0.29	0	0	0	0	1
Δ(Date)		26.87	24.19	0	10	25	28	127		27.64	24.43	0	11	25	28	127
I(Rel.)		0.03	0.18	0	0	0	0	1		0.03	0.18	0	0	0	0	1
Rel. (N. Loans)		0.04	0.25	0	0	0	0	8		0.04	0.25	0	0	0	0	8
Rel. (A. Loan)		18	3,074	0	0	0	0	680,000		20	3,187	0	0	0	0	680,000
BC		52.08	96.02	1	8	23	59	3,655		50.98	91.22	1	8	23	58	3,655
GS_{zip}		4,236	5,079	1	220	1,295	8,979	16,637		4,362	5,140	1	225	1,354	10,684	16,637
GS_{city}		2,715	3,252	1	159	835	6,096	11,415		2,797	3,294	1	162	886	6,458	11,415
I(New Bank)	82,287	0.04	0.20	0	0	0	0	1	76,082	0.04	0.20	0	0	0	0	1
I(CU)	85,351	0.03	0.18	0	0	0	0	1	79,147	0.03	0.18	0	0	0	0	1
I(CD)	82,821	0.01	0.08	0	0	0	0	1	76,605	0.01	0.08	0	0	0	0	1

Table 1 Summary Statistics (Cont.)

Restaurant and Lender Characteristics – Cross Section (Cont.)

	Panel B: 2021 PPP First Draw															
	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
I(Minority)	6,268	0.38	0.49	0	0	0	1	1	6,024	0.39	0.49	0	0	0	1	1
I(African Ame.)		0.01	0.11	0	0	0	0	1		0.01	0.12	0	0	0	0	1
I(Asian)		0.22	0.41	0	0	0	0	1		0.22	0.42	0	0	0	0	1
I(Hispanic)		0.15	0.36	0	0	0	0	1		0.16	0.36	0	0	0	0	1
Employment		9.39	13.41	1	3	6	11	342		8.41	8.66	1	3	6	10	93
I(Franchise)		0.06	0.23	0	0	0	0	1		0.06	0.23	0	0	0	0	1
I(Fintech)		0.17	0.38	0	0	0	0	1		0.18	0.38	0	0	0	0	1
Δ(Date)		41.12	21.14	0	23	39	60	78		41.01	21.05	0	23	39	60	78
I(Rel.)		0.02	0.13	0	0	0	0	1		0.02	0.13	0	0	0	0	1
Rel. (N. Loans)		0.02	0.16	0	0	0	0	3		0.02	0.15	0	0	0	0	3
Rel. (A. Loan)		0.00	0.06	0	0	0	0	3		0.00	0.06	0	0	0	0	3
BC		33.01	64.64	1	5	14	38	2,095		32.60	59.53	1	5	14	38	2,095
GS_{zip}		5,702	5,875	1	266	3,275	10,972	16,637		5,808	5,893	1	284	3,381	10,972	16,637
GS_{city}		3,707	3,872	1	188	2,200	6,595	11,415		3,775	3,885	1	195	2,225	6,595	11,415
I(New Bank)	4,866	0.04	0.20	0	0	0	0	1	4,648	0.04	0.20	0	0	0	0	1
I(CU)	4,962	0.02	0.14	0	0	0	0	1	4,741	0.02	0.14	0	0	0	0	1
I(CD)	5,299	0.05	0.21	0	0	0	0	1	5,080	0.05	0.21	0	0	0	0	1

Table 1.2 Restaurant Ratings – Restaurant-Level Panel

	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
Panel A: 2020 PPP First Draw																
Before Covid-19																
Rating Stars	1,032,002	3.84	1.21	1	3	4	5	5	959,322	3.84	1.20	1	3	4	5	5
During Covid-19																
Rating Stars	464,639	3.92	1.29	1	3	4	5	5	432,599	3.93	1.29	1	3	4	5	5
Panel B: 2021 PPP First Draw																
Before Covid-19																
Rating Stars	51,845	3.95	1.22	1	3	4	5	5	50,103	3.95	1.22	1	3	4	5	5
During Covid-19																
Rating Stars	26,492	4.06	1.25	1	4	5	5	5	25,477	4.06	1.25	1	4	5	5	5

Table 2 Fintech Lenders and Minority Borrowers

This table reports the linear probability regression results where the dependent variable is the *Fintech* loan indicator (0/1). In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. *Minority*, *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, the same business type (aggregated), the same food price range, and of an employment size with a difference of at most five employees. In addition to the variables reported in the table, we also control for city and business type fixed effects. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	*I*(Fintech) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	4.78***	3.61***	4.55***	3.47***				
	(0.28)	(0.29)	(0.28)	(0.29)				
I(African Ame.)					8.00***	4.99***	7.64***	4.86***
					(1.59)	(1.67)	(1.64)	(1.71)
I(Asian)					7.43***	6.07***	7.08***	5.84***
					(0.38)	(0.40)	(0.38)	(0.40)
I(Hispanic)					0.88***	0.06	0.82**	0.04
					(0.32)	(0.32)	(0.32)	(0.33)
Employment	-0.07***	-0.07***	-0.15***	-0.15***	-0.06***	-0.06***	-0.14***	-0.14***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
I(Franchise)	-0.43	-0.32	-0.10	-0.25	-0.31	-0.23	0.02	-0.16
	(0.32)	(0.33)	(0.36)	(0.38)	(0.32)	(0.34)	(0.36)	(0.38)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	92,556	88,873	86,095	82,426	92,556	88,873	86,095	82,426
Adjusted R^2	0.037	0.058	0.039	0.060	0.041	0.062	0.042	0.062

Panel B: 2021 PPP First Draw

Dep. Var.	*I*(Fintech) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	8.24***	4.99***	7.96***	4.95***				
	(1.06)	(1.46)	(1.08)	(1.48)				
I(African Ame.)					16.18***	5.52	16.07***	6.62
					(5.05)	(6.08)	(5.07)	(6.01)
I(Asian)					10.14***	6.10***	9.60***	5.67***
					(1.33)	(1.80)	(1.34)	(1.82)
I(Hispanic)					4.95***	3.31*	5.04***	3.71*
					(1.42)	(1.93)	(1.44)	(1.98)
Employment	-0.15***	-0.13***	-0.28***	-0.30***	-0.14***	-0.12***	-0.26***	-0.30***
	(0.03)	(0.05)	(0.05)	(0.07)	(0.03)	(0.05)	(0.05)	(0.07)
I(Franchise)	-3.03*	-7.78***	-2.47	-6.93**	-2.95*	-7.72***	-2.42	-6.90**
	(1.78)	(2.73)	(1.88)	(2.84)	(1.78)	(2.74)	(1.88)	(2.85)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	6,266	4,150	6,022	3,984	6,266	4,150	6,022	3,984
Adjusted R^2	0.059	0.078	0.059	0.085	0.061	0.078	0.061	0.084

Table 3 Restaurant Ratings

This table reports the regression results examining the difference in ratings between minority- and non-minority-owned restaurants that borrow from fintech and non-fintech lenders (i.e., the fintech-minority double difference). In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, within a range of 0 to 5, based on the customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, the same business type (aggregated), the same food price range, and of an employment size with a difference of at most five employees. In addition to the variables reported in the table, we also control for city × month (or month) fixed effects, business type fixed effects, and eating policy dummies for options of delivery, takeout, reservations, and outdoor seating. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	**Rating Stars**							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(Fintech)	-0.11	-0.09	-0.11	-0.09	-0.25**	-0.23**	-0.24**	-0.23**
	(0.07)	(0.08)	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)	(0.11)
I(Asian) × *I*(Fintech)	-0.08***	-0.09***	-0.08***	-0.09***	-0.06***	-0.04*	-0.06***	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
I(Hisp.) × *I*(Fintech)	-0.01	0.01	-0.01	0.01	-0.02	0.00	-0.02	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
I(Fintech)	0.05***	0.06***	0.05***	0.06***	0.05***	0.04***	0.05***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(African Ame.)	0.12***	0.15***	0.11***	0.14***	0.05	0.06	0.04	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
I(Asian)	-0.09***	-0.07***	-0.09***	-0.08***	-0.03***	-0.03***	-0.04***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Hisp.)	-0.09***	-0.09***	-0.09***	-0.09***	-0.11***	-0.11***	-0.11***	-0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Employment	-0.12***	-0.12***	-0.22***	-0.21***	-0.11***	-0.12***	-0.19***	-0.19***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
I(Franchise)	-0.89***	-0.87***	-0.88***	-0.85***	-1.06***	-1.02***	-1.05***	-1.00***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Eating Policy Controls	X	X	X	X	X	X	X	X
Observations	1,032,002	974,781	959,322	902,934	464,639	434,948	432,598	403,363
Adjusted R^2	0.046	0.067	0.043	0.064	0.052	0.072	0.048	0.069

Table 3 Restaurant Ratings (Cont.)

Panel B: 2021 PPP First Draw								
Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(Fintech)	-0.13	-0.31	-0.12	-0.30	-0.14	-0.29	-0.12	-0.26
	(0.17)	(0.20)	(0.17)	(0.21)	(0.18)	(0.21)	(0.18)	(0.21)
I(Asian) × *I*(Fintech)	0.02	0.08	0.03	0.10	-0.02	0.01	-0.00	0.03
	(0.06)	(0.09)	(0.06)	(0.09)	(0.07)	(0.10)	(0.07)	(0.10)
I(Hispanic) × *I*(Fintech)	0.08	0.13	0.08	0.13	-0.18**	-0.28**	-0.19**	-0.27**
	(0.07)	(0.11)	(0.07)	(0.11)	(0.09)	(0.13)	(0.09)	(0.13)
I(Fintech)	-0.06	-0.07	-0.07*	-0.08	-0.06	-0.01	-0.06	-0.02
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
I(African Ame.)	0.16	0.31**	0.15	0.31**	-0.05	-0.01	-0.05	-0.01
	(0.11)	(0.13)	(0.11)	(0.12)	(0.11)	(0.13)	(0.11)	(0.13)
I(Asian)	-0.13***	-0.13***	-0.14***	-0.14***	-0.04	-0.01	-0.04	-0.01
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.13***	-0.10**	-0.12***	-0.09*	-0.16***	-0.09*	-0.15***	-0.08
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)
Employment	-0.34***	-0.32**	-0.72***	-0.82***	-0.38***	-0.42**	-0.60***	-0.82***
	(0.10)	(0.15)	(0.11)	(0.18)	(0.10)	(0.18)	(0.12)	(0.19)
I(Franchise)	-0.91***	-0.84***	-0.88***	-0.79***	-0.91***	-0.81***	-0.90***	-0.77***
	(0.06)	(0.08)	(0.06)	(0.08)	(0.07)	(0.10)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Eating Policy Controls	X	X	X	X	X	X	X	X
Observations	51,844	29,256	50,102	28,211	26,491	14,723	25,476	14,095
Adjusted R^2	0.039	0.049	0.039	0.050	0.041	0.050	0.039	0.047

Table 4 Previous Lending Relationships (Matched Sample)

This table reports the regression results examining the difference in previous lending relationships between minority- and non-minority-owned restaurants. In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable in columns (1) and (2) is a dummy variable that equals 1 if the borrower has borrowed SBA 7(a) or 504 loans during 2009-2019. In columns (3) and (4) ((5) and (6)), the dependent variable is the total number (million amount) of SBA 7(a) or 504 loans borrowed during 2009-2019. *A. Loan* is winsorized at the 1% and 99% cuts. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, all dependent variables are multiplied by 100, and *Employment* is divided by 100. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*I*(Rel.) × 100	*I*(Rel.) × 100	Rel. (N. Loans) × 100	Rel. (N. Loans) × 100	Rel. (A. Loan) × 100	Rel. (A. Loan) × 100
I(African Ame.)	-0.76	-0.87	-0.91	-1.20	-0.04	-0.21
	(0.66)	(0.68)	(1.09)	(1.13)	(0.33)	(0.34)
I(Asian)	-0.72***	-1.00***	-1.09***	-1.42***	-0.06	-0.23**
	(0.16)	(0.18)	(0.22)	(0.26)	(0.08)	(0.09)
I(Hispanic)	-1.11***	-1.03***	-1.60***	-1.40***	-0.25***	-0.30***
	(0.15)	(0.17)	(0.20)	(0.21)	(0.09)	(0.09)
Employment	2.34***	2.11***	3.56***	3.21***	2.99***	2.96***
	(0.43)	(0.45)	(0.59)	(0.61)	(0.32)	(0.34)
I(Franchise)	3.87***	3.83***	4.06***	3.98***	2.10***	1.99***
	(0.29)	(0.31)	(0.38)	(0.41)	(0.17)	(0.18)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	86,095	82,426	86,095	82,426	86,095	82,426
Adjusted R^2	0.011	0.008	0.009	0.004	0.011	-0.010

Panel B: 2021 PPP First Draw

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*I*(Rel.) × 100	*I*(Rel.) × 100	Rel. (N. Loans) × 100	Rel. (N. Loans) × 100	Rel. (A. Loan) × 100	Rel. (A. Loan) × 100
I(African Ame.)	0.71	1.89	0.42	1.59	-0.24	-0.15
	(1.71)	(2.35)	(1.72)	(2.39)	(0.20)	(0.29)
I(Asian)	-0.47	-0.07	-0.70	-0.06	-0.23**	-0.36*
	(0.40)	(0.57)	(0.46)	(0.65)	(0.10)	(0.21)
I(Hispanic)	-0.69	-0.02	-0.90*	0.02	-0.23	-0.15
	(0.45)	(0.67)	(0.52)	(0.79)	(0.16)	(0.22)
Employment	3.40	4.95	3.63	5.63	2.94**	4.40**
	(2.13)	(3.34)	(2.58)	(4.36)	(1.16)	(2.10)
I(Franchise)	1.43	1.61	1.75	2.27	0.35	0.60
	(0.99)	(1.25)	(1.23)	(1.67)	(0.34)	(0.49)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	6,022	3,984	6,022	3,984	6,022	3,984
Adjusted R^2	0.005	-0.011	0.004	-0.028	0.003	-0.095

Table 5 Business Capital (Matched Sample)

This table reports the regression results examining the impact of business capital on the fintech-minority double difference in ratings. The 2020 and 2021 waves are indicated in column heads. The dependent variable is the *Rating Stars*, within a range of 0 to 5, based on the customer ratings from yelp.com. Business capital (*BC*) is proxied by the total number of ratings in the entire period of our analysis (from April 2018 to March 2021). *BC* is divided by 100 for demonstration purposes and winsorized at the 99% cuts. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021.Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(FT) × BC	0.07	0.07*	0.03	0.03	0.00	-0.07	-0.00	0.04
	(0.04)	(0.04)	(0.13)	(0.11)	(0.09)	(0.12)	(0.09)	(0.12)
I(Asia.) × *I*(FT) × BC	0.11***	0.10***	0.08***	0.07***	0.24***	0.28***	0.12***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.05)	(0.04)	(0.05)
I(Hisp.) × *I*(FT) × BC	0.13***	0.12***	0.09***	0.08***	0.06	-0.00	-0.08	-0.18
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.09)	(0.08)	(0.11)
I(FT)	-0.02***	-0.01	-0.02	-0.01	-0.11***	-0.11**	-0.12***	-0.10*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
I(African Ame.)	0.09***	0.13***	-0.00	0.01	0.11	0.25**	-0.08	-0.09
	(0.03)	(0.03)	(0.04)	(0.04)	(0.10)	(0.12)	(0.10)	(0.12)
I(Asian)	-0.11***	-0.10***	-0.05***	-0.05***	-0.17***	-0.16***	-0.06**	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.10***	-0.10***	-0.12***	-0.11***	-0.11***	-0.06	-0.18***	-0.12**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
Employment	-0.22***	-0.21***	-0.19***	-0.20***	-0.75***	-0.84***	-0.61***	-0.84***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.11)	(0.18)	(0.13)	(0.19)
I(Franchise)	-0.87***	-0.85***	-1.05***	-1.00***	-0.88***	-0.78***	-0.90***	-0.78***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)	(0.08)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	959,322	902,934	432,598	403,363	50,102	28,211	25,476	14,095
Adjusted R^2	0.044	0.064	0.049	0.069	0.041	0.053	0.040	0.048

Table 6 Relative Geographic Lending Scope (Matched Sample)

This table reports the regression results examining the impact of geographic lending scope on the fintech-minority double difference in ratings. The 2020 and 2021 waves are indicated in column heads. CDFIs and CDCs are excluded because their lending scope may be restricted to certain communities. The dependent variable is the *Rating Stars*, within a range of 0 to 5, based on the customer ratings from yelp.com. Relative geographic lending scope (GS_r) is calculated as the total number of zip codes divided by the total number of cities that the lender covers in the entire PPP sample. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.)×I(FT)×GS_r	-0.07	-0.06	-0.15**	-0.15**	-0.07	-0.21	-0.07	-0.17
	(0.05)	(0.05)	(0.07)	(0.07)	(0.11)	(0.14)	(0.12)	(0.15)
I(Asian)×I(FT)×GS_r	-0.06***	-0.06***	-0.04***	-0.03**	0.02	0.06	-0.00	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(Hisp.)×I(FT)×GS_r	-0.00	0.01	-0.01	-0.00	0.05	0.06	-0.12**	-0.18**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.07)	(0.06)	(0.09)
I(FT)	0.05***	0.06***	0.05***	0.04***	-0.07*	-0.07	-0.06	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(African Ame.)	0.11***	0.14***	0.03	0.04	0.14	0.32**	-0.06	-0.02
	(0.03)	(0.03)	(0.04)	(0.04)	(0.11)	(0.13)	(0.12)	(0.14)
I(Asian)	-0.09***	-0.08***	-0.04***	-0.04***	-0.14***	-0.14***	-0.04	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.09***	-0.09***	-0.11***	-0.11***	-0.12***	-0.08*	-0.15***	-0.09
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.04)	(0.06)
Employment	-0.21***	-0.21***	-0.19***	-0.19***	-0.71***	-0.83***	-0.60***	-0.81***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.11)	(0.18)	(0.13)	(0.19)
I(Franchise)	-0.88***	-0.86***	-1.05***	-1.00***	-0.88***	-0.77***	-0.90***	-0.77***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)	(0.08)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	952,731	896,408	429,480	400,262	49,403	27,632	25,036	13,745
Adjusted R^2	0.044	0.064	0.049	0.069	0.039	0.049	0.039	0.047

Table 7 First-Time Banks and Minority Borrowers

This table reports the linear probability regression results where the dependent variable is the *New Bank* loan indicator (0/1) that equals one if the lender is a first-time bank in SBA programs. We use the SBA 7(a) and 504 loan-level data from 1990-2019 to identify lenders that participated in SBA programs before. We exclude fintech lenders and non-banks. In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	*I*(New Bank) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	-1.42***	-0.83***	-1.43***	-0.84***				
	(0.18)	(0.18)	(0.18)	(0.19)				
I(African Ame.)					-0.63	0.20	-0.54	0.44
					(0.92)	(0.93)	(0.94)	(0.96)
I(Asian)					-2.23***	-1.40***	-2.21***	-1.39***
					(0.21)	(0.21)	(0.21)	(0.21)
I(Hispanic)					-0.40	-0.12	-0.45*	-0.17
					(0.25)	(0.24)	(0.25)	(0.25)
Employment	-0.01***	-0.00***	-0.00	0.00	-0.01***	-0.01***	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I(Franchise)	-0.39	-0.05	-0.32	-0.07	-0.42	-0.07	-0.35	-0.09
	(0.26)	(0.27)	(0.29)	(0.30)	(0.26)	(0.27)	(0.29)	(0.30)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	82,285	78,589	76,080	72,390	82,285	78,589	76,080	72,390
Adjusted R^2	0.001	0.132	0.001	0.133	0.002	0.132	0.002	0.133

Panel B: 2021 PPP First Draw

Dep. Var.	*I*(New Bank) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	-0.74	0.13	-0.76	0.14				
	(0.67)	(0.84)	(0.68)	(0.87)				
I(African Ame.)					5.31	7.54	5.13	7.36
					(6.32)	(7.76)	(6.43)	(7.87)
I(Asian)					-2.54***	-1.82**	-2.48***	-1.84**
					(0.71)	(0.79)	(0.71)	(0.83)
I(Hispanic)					1.11	1.98	0.99	2.09
					(1.05)	(1.53)	(1.06)	(1.58)
Employment	0.01	-0.01	0.04	-0.01	0.01	-0.01	0.03	-0.02
	(0.02)	(0.02)	(0.04)	(0.04)	(0.02)	(0.02)	(0.04)	(0.04)
I(Franchise)	-1.13	0.84	-1.28	0.65	-1.13	0.77	-1.26	0.60
	(1.07)	(1.66)	(1.13)	(1.77)	(1.07)	(1.67)	(1.13)	(1.78)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	4,865	2,950	4,647	2,815	4,865	2,950	4,647	2,815
Adjusted R^2	0.001	0.092	0.001	0.088	0.005	0.098	0.004	0.094

Table 8 Restaurant Ratings (First-Time Banks)

This table reports the regression results examining the difference in ratings between minority- and non-minority-owned restaurants that borrow from lenders who are first-time banks and from lenders who participated in SBA programs before. We use the SBA 7(a) and 504 loan-level data from 1990-2019 to identify lenders that participated in SBA programs before. We exclude fintech lenders and non-banks. In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, within a range of 0 to 5, based on the customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The variable *New Bank* is defined to be 1 if the lender is a first-time bank in SBA programs. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(New Bank)	-0.09	-0.07	-0.08	-0.07	0.09	0.07	0.09	0.05
	(0.13)	(0.16)	(0.13)	(0.16)	(0.15)	(0.19)	(0.14)	(0.19)
I(Asian) × *I*(New Bank)	-0.05	-0.02	-0.05	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
I(Hisp.) × *I*(New Bank)	0.02	0.02	0.00	0.01	0.03	0.02	0.02	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
I(New Bank)	0.04**	0.03	0.04**	0.03	-0.00	0.00	0.00	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	915,513	858,150	845,747	789,355	411,222	381,574	380,498	351,392
Adjusted R^2	0.047	0.069	0.044	0.066	0.052	0.073	0.049	0.069

Panel B: 2021 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(New Bank)	0.71***	0.41	0.66***	0.42*	0.44*	0.30	0.41*	0.31
	(0.15)	(0.25)	(0.15)	(0.24)	(0.24)	(0.31)	(0.24)	(0.31)
I(Asian) × *I*(New Bank)	0.29**	0.16	0.28*	0.18	-0.06	0.14	-0.09	0.07
	(0.15)	(0.30)	(0.15)	(0.30)	(0.16)	(0.35)	(0.16)	(0.37)
I(Hisp.) × *I*(New Bank)	-0.11	-0.25	-0.09	-0.27	-0.25	-0.32	-0.28	-0.37
	(0.13)	(0.22)	(0.13)	(0.22)	(0.18)	(0.32)	(0.18)	(0.33)
I(New Bank)	-0.04	0.15	-0.04	0.13	0.19***	0.24*	0.22***	0.27*
	(0.08)	(0.18)	(0.08)	(0.17)	(0.07)	(0.13)	(0.07)	(0.14)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	39,695	20,147	38,183	19,342	20,145	10,090	19,275	9,592
Adjusted R^2	0.041	0.055	0.041	0.057	0.043	0.051	0.040	0.049

Table 9 Credit Unions and Minority Borrowers

This table reports the linear probability regression results where the dependent variable is the *CU* loan indicator (0/1) that equals one if the lender is a credit union. We restrict to the sample matched with FFEIC. In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	*I*(CU) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	-0.75***	-0.60***	-0.73***	-0.63***				
	(0.16)	(0.17)	(0.16)	(0.18)				
I(African Ame.)					1.87*	2.39**	1.90*	2.50**
					(1.02)	(1.02)	(1.05)	(1.04)
I(Asian)					-1.47***	-1.50***	-1.49***	-1.57***
					(0.17)	(0.21)	(0.17)	(0.21)
I(Hispanic)					0.15	0.51**	0.21	0.53**
					(0.27)	(0.25)	(0.27)	(0.26)
Employment	-0.02***	-0.02***	-0.03***	-0.03***	-0.02***	-0.02***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I(Franchise)	-1.06***	-0.81***	-1.05***	-0.77***	-1.09***	-0.83***	-1.08***	-0.80***
	(0.19)	(0.20)	(0.20)	(0.21)	(0.19)	(0.20)	(0.20)	(0.21)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	85,349	81,702	79,145	75,502	85,349	81,702	79,145	75,502
Adjusted R^2	0.003	0.098	0.003	0.097	0.004	0.099	0.004	0.098

Panel B: 2021 PPP First Draw

Dep. Var.	*I*(CU) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	-1.27**	-1.25	-1.41**	-1.23				
	(0.65)	(0.81)	(0.64)	(0.82)				
I(African Ame.)					6.48	7.42	6.10	7.09
					(5.75)	(6.55)	(5.70)	(6.57)
I(Asian)					-2.06***	-2.68***	-2.18***	-2.79***
					(0.71)	(0.87)	(0.72)	(0.90)
I(Hispanic)					-0.73	0.03	-0.87	0.28
					(0.94)	(1.34)	(0.94)	(1.35)
Employment	-0.02	-0.04	-0.07**	-0.12***	-0.03	-0.04	-0.08**	-0.13***
	(0.02)	(0.03)	(0.03)	(0.05)	(0.02)	(0.03)	(0.03)	(0.05)
I(Franchise)	-1.24	1.26	-1.48	1.04	-1.22	1.28	-1.45	1.08
	(1.12)	(1.72)	(1.11)	(1.75)	(1.12)	(1.72)	(1.11)	(1.75)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	5,298	3,321	5,079	3,184	5,298	3,321	5,079	3,184
Adjusted R^2	0.002	0.065	0.007	0.079	0.004	0.069	0.008	0.083

Table 10 Restaurant Ratings (Credit Unions)

This table reports the regression results examining the difference in ratings between minority- and non-minority-owned restaurants that borrow from credit unions and from other lenders in the FFIEC list. We restrict to the sample matched with FFEIC. In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, within a range of 0 to 5, based on the customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *CU* is defined to be 1 if the lender is a credit union. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)× *I*(CU)	-0.06	-0.08	-0.06	-0.07	-0.13	0.03	-0.12	0.04
	(0.11)	(0.13)	(0.11)	(0.12)	(0.18)	(0.16)	(0.18)	(0.16)
I(Asian) × *I*(CU)	-0.03	-0.04	-0.04	-0.04	-0.13***	-0.12**	-0.12***	-0.11**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
I(Hispanic) × *I*(CU)	0.01	0.01	-0.00	0.01	0.01	0.01	0.00	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
I(CU)	0.09***	0.09***	0.10***	0.10***	0.11***	0.11***	0.11***	0.11***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	952,321	895,771	882,486	826,845	427,705	398,417	396,912	368,112
Adjusted R^2	0.047	0.068	0.044	0.065	0.052	0.073	0.049	0.069

Panel B: 2021 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)× *I*(CU)	0.65***	0.47**	0.67***	0.54***	0.48**	0.61**	0.50**	0.70**
	(0.13)	(0.20)	(0.13)	(0.20)	(0.20)	(0.27)	(0.20)	(0.28)
I(Asian) × *I*(CU)	0.08	-0.14	0.12	-0.12	-0.01	0.12	0.00	0.17
	(0.11)	(0.18)	(0.11)	(0.17)	(0.13)	(0.23)	(0.13)	(0.24)
I(Hispanic) × *I*(CU)	-0.18	-0.29	-0.11	-0.26	-0.01	0.26	-0.01	0.29
	(0.15)	(0.18)	(0.15)	(0.18)	(0.14)	(0.27)	(0.15)	(0.27)
I(CU)	0.09	0.19**	0.04	0.12	0.11*	-0.11	0.10	-0.18
	(0.06)	(0.09)	(0.06)	(0.10)	(0.07)	(0.14)	(0.07)	(0.14)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	43,203	22,546	41,716	21,715	21,815	11,194	20,931	10,694
Adjusted R^2	0.040	0.049	0.040	0.049	0.041	0.042	0.038	0.037

Table 11 CDFIs/CDCs and Minority Borrowers

This table reports the linear probability regression results of specifications where the dependent variable is the *CDC* loan indicator (0/1) that equals one if the lender is a CDFI or CDC. We exclude fintech lenders and other non-banks. In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	*I*(CDC) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	0.50***	0.35***	0.49***	0.34***				
	(0.09)	(0.10)	(0.10)	(0.10)				
I(African Ame.)					2.37***	2.27***	2.38***	2.33***
					(0.77)	(0.81)	(0.79)	(0.83)
I(Asian)					0.32***	0.15	0.29***	0.11
					(0.09)	(0.10)	(0.09)	(0.10)
I(Hispanic)					0.65***	0.53***	0.66***	0.55***
					(0.16)	(0.17)	(0.16)	(0.18)
Employment	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I(Franchise)	-0.15**	-0.04	-0.14*	-0.04	-0.15**	-0.05	-0.14*	-0.04
	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	82,819	79,121	76,603	72,910	82,819	79,121	76,603	72,910
Adjusted R^2	0.002	-0.014	0.002	-0.016	0.002	-0.013	0.002	-0.016

Panel B: 2021 PPP First Draw

Dep. Var.	*I*(CDC) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	0.14	-1.11*	0.03	-1.33**				
	(0.42)	(0.64)	(0.41)	(0.65)				
I(African Ame.)					5.74	3.25	5.84	3.34
					(3.70)	(3.82)	(3.76)	(3.88)
I(Asian)					-0.50	-1.76**	-0.60	-2.07***
					(0.44)	(0.73)	(0.46)	(0.74)
I(Hispanic)					0.53	-0.74	0.41	-0.87
					(0.67)	(0.87)	(0.62)	(0.83)
Employment	-0.01	-0.02	-0.04**	-0.05*	-0.01	-0.02	-0.04**	-0.06*
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
I(Franchise)	-0.61	-2.51**	-0.46	-2.52**	-0.60	-2.53**	-0.44	-2.53**
	(0.83)	(1.22)	(0.88)	(1.07)	(0.83)	(1.22)	(0.88)	(1.07)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	4,961	3,033	4,740	2,890	4,961	3,033	4,740	2,890
Adjusted R^2	0.001	0.014	0.001	0.005	0.003	0.015	0.003	0.006

Table 12 Restaurant Ratings (CDFIs/CDCs)

This table reports the regression results examining the difference in ratings between minority- and non-minority-owned restaurants that borrow from community development oriented lenders and from banks. We exclude fintech lenders and other non-banks. In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, within a range of 0 to 5, based on the customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The variable *CDC* is defined to be 1 if the lender is a CDFI or CDC. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri. Ame.)× *I*(CDC)	-0.04	-0.04	-0.05	-0.03	0.05	-0.01	0.05	-0.01
	(0.11)	(0.12)	(0.11)	(0.12)	(0.15)	(0.17)	(0.15)	(0.17)
I(Asian) × *I*(CDC)	-0.24***	-0.21***	-0.23***	-0.20***	-0.07	-0.08	-0.07	-0.09
	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.09)	(0.08)	(0.09)
I(Hispanic) × *I*(CDC)	-0.05	0.04	-0.06	0.04	0.06	0.11	0.05	0.11
	(0.07)	(0.07)	(0.07)	(0.08)	(0.09)	(0.10)	(0.09)	(0.10)
I(CDC)	0.20***	0.16***	0.20***	0.16***	0.07	0.04	0.07	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	921,932	864,501	852,090	795,599	414,237	384,558	383,485	354,350
Adjusted R^2	0.047	0.069	0.044	0.065	0.052	0.073	0.048	0.069

Panel B: 2021 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri. Ame.)× *I*(CDC)	0.05	-0.22	0.06	-0.23	0.23	0.22	0.26	0.23
	(0.20)	(0.32)	(0.20)	(0.31)	(0.29)	(0.36)	(0.28)	(0.35)
I(Asian) × *I*(CDC)	0.04	0.17	0.09	0.15	-0.30	-0.09	-0.25	-0.18
	(0.12)	(0.21)	(0.11)	(0.21)	(0.19)	(0.29)	(0.19)	(0.28)
I(Hispanic) × *I*(CDC)	-0.02	-0.10	0.01	0.06	-0.06	0.32	-0.03	0.45
	(0.15)	(0.28)	(0.15)	(0.31)	(0.19)	(0.28)	(0.20)	(0.28)
I(CDC)	0.13	0.15	0.09	0.11	0.17**	0.05	0.12	0.03
	(0.09)	(0.13)	(0.09)	(0.13)	(0.08)	(0.12)	(0.08)	(0.12)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	40,425	20,707	38,882	19,848	20,611	10,450	19,715	9,915
Adjusted R^2	0.041	0.056	0.041	0.058	0.042	0.053	0.039	0.049

Table 13 Approval Date

This table reports the regression results examining the difference in PPP loan approval dates between minority- and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. The dependent variable is the *Δ(Approval Date-PPP Starting Date)*, where the starting date is April 03,2020 for the 2020 wave and Jan 12, 2021 for the 2021 wave. The 2020 and 2021 waves are indicated in column heads. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Δ(Approval Date-PPP Starting Date)							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(Fintech)	-3.30	-2.20	-3.12	-2.01	-3.61	-0.01	-3.82	-0.04
	(3.10)	(3.25)	(3.10)	(3.26)	(4.13)	(4.65)	(4.14)	(4.69)
I(Asian) × *I*(Fintech)	2.23***	3.11***	2.52***	3.39***	-8.11***	-7.34***	-8.20***	-7.54***
	(0.74)	(0.76)	(0.74)	(0.77)	(1.57)	(2.16)	(1.58)	(2.17)
I(Hispanic) × *I*(Fintech)	0.80	0.06	0.83	0.11	-8.72***	-6.71**	-8.75***	-6.83**
	(1.12)	(1.15)	(1.11)	(1.15)	(2.04)	(2.64)	(2.06)	(2.68)
I(Fintech)	14.31***	11.93***	13.63***	11.27***	2.42**	0.66	2.38**	0.50
	(0.47)	(0.52)	(0.48)	(0.52)	(0.94)	(1.28)	(0.96)	(1.30)
I(African Ame.)	9.63***	7.61***	8.88***	6.86***	8.71***	4.35	8.91***	4.56
	(1.23)	(1.29)	(1.24)	(1.29)	(2.65)	(2.98)	(2.72)	(3.06)
I(Asian)	10.37***	9.08***	9.72***	8.47***	2.43***	1.42	2.29***	1.28
	(0.32)	(0.33)	(0.31)	(0.33)	(0.77)	(1.09)	(0.78)	(1.10)
I(Hispanic)	5.47***	4.98***	5.30***	4.84***	3.15***	2.51*	3.18***	2.50*
	(0.28)	(0.28)	(0.28)	(0.29)	(0.89)	(1.30)	(0.90)	(1.33)
Employment	-0.09***	-0.09***	-0.20***	-0.19***	-0.05**	-0.05	-0.12***	-0.14***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
I(Franchise)	-8.15***	-7.91***	-7.93***	-7.89***	1.21	0.92	1.62	1.84
	(0.20)	(0.21)	(0.22)	(0.23)	(1.14)	(1.59)	(1.19)	(1.61)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	92,556	88,873	86,095	82,426	6,266	4,150	6,022	3,984
Adjusted R^2	0.140	0.176	0.142	0.176	0.030	0.036	0.019	0.025

Table 14 Restaurant Ratings (Robustness –Approval Date Fixed Effects)

This table reports the robustness check results of Table 3 which examine the difference in ratings between minority- and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. We add approval date fixed effects as control variables. Other than that, the specifications are the same as in Table 3. In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, within a range of 0 to 5, based on the customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and other control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afr.) × *I*(Fintech)	-0.11	-0.09	-0.11	-0.08	-0.25**	-0.23**	-0.25**	-0.23**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)	(0.11)
I(Asian) × *I*(Fintech)	-0.08***	-0.08***	-0.08***	-0.08***	-0.06***	-0.04	-0.06***	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
I(Hispanic) × *I*(Fintech)	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.02	-0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
I(Fintech)	0.06***	0.06***	0.06***	0.06***	0.05***	0.04**	0.05***	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	1032002	974781	959322	902934	464638	434947	432597	403362
Adjusted R^2	0.047	0.068	0.044	0.065	0.052	0.073	0.049	0.069

Panel B: 2021 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afr.) × *I*(Fintech)	-0.12	-0.32	-0.13	-0.35	-0.10	-0.25	-0.10	-0.27
	(0.17)	(0.21)	(0.16)	(0.21)	(0.18)	(0.21)	(0.18)	(0.22)
I(Asian) × *I*(Fintech)	0.01	0.08	0.01	0.09	-0.02	0.02	-0.01	0.05
	(0.06)	(0.09)	(0.06)	(0.09)	(0.07)	(0.10)	(0.07)	(0.10)
I(Hispanic) × *I*(Fintech)	0.07	0.11	0.07	0.10	-0.17**	-0.28**	-0.17**	-0.28**
	(0.07)	(0.11)	(0.07)	(0.11)	(0.09)	(0.13)	(0.09)	(0.13)
I(Fintech)	-0.07*	-0.07	-0.08*	-0.09	-0.07	-0.01	-0.07*	-0.02
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.07)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	51844	29256	50102	28211	26491	14721	25476	14093
Adjusted R^2	0.042	0.054	0.042	0.056	0.043	0.057	0.042	0.054

Appendix

Table A1 Variable Definition

Variable Name	Definition	Data Source
I(Fintech)	1 if the lender of the loan is a fintech lender, 0 otherwise	• PPP loan-level dataset • Consolidated fintech company list
I(Minority) *I*(African Ame.) *I*(Asian) *I*(Hispanic)	1 if the restaurant is a minority-led one, 0 otherwise 1 if the restaurant is a African American-led one, 0 otherwise 1 if the restaurant is a Asian-led one (including pacific islander), 0 otherwise 1 if the restaurant is a Hispanic-led one, 0 otherwise *When multiple food categories, African American ≳ Asian ≳ Hispanic.*	• yelp.com • food type classification list
Rating Stars	Mean of all the customer ratings in the month within the range of 0 to 5	• yelp.com
Eating Policy	Dummies for the following restaurant amenities: delivery, takeout, reservations, and outdoor seating	
Food Price	Dummies for $,$$,$$$,$$$$	
BC	Business Capital: the total number of ratings in the entire period of our analysis (from April 2018 to March 2021)	
Δ(Approval Date-PPP Starting Date)	Number of days between the date approved and April 3rd, 2020 for the 2020 PPP number of days between the date approved and Jan 12th, 2021 for the 2021 PPP	• PPP loan-level dataset
Employment	*Jobs Reported* in the SBA original dataset	
I(Franchise)	1 if the *Franchise Name* in the SBA original dataset is non-empty after our adjustments (see Online Appendix C3)	
Business Type FEs	Dummies based Business Type in the SBA original dataset, including the types of : Cooperative Corporation, Employee Stock Ownership Plan(ESOP), Independent Contractors, Joint Venture, Limited Liability Company(LLC), Limited Liability Partnership, Partnership, Professional Association, Qualified Joint-Venture (spouses), Self-Employed Individuals, Single Member LLC, Sole Proprietorship, Subchapter S Corporation, Tenant in Common, Tribal Concerns, Trust	
Approval Date FEs	Dummies for the Approval Date in the SBA original dataset	
GS_{zip}	the total number of zip codes that the lender covers in the entire PPP loan sample	
GS_{city}	the total number of cities that the lender covers in the entire PPP loan sample	
City FEs	Dummies for cities Convert zip code in the SBA original dataset to city using the HUD-USPS ZIP Code Crosswalk data. If the zip code-city conversion is not available in the HUD data, we manually searched and find the city in the format in the HUD data. *We do not directly use the city information in the PPP data due to quality concerns.*	• PPP loan-level dataset • HUD User
New Bank	1 if the lender is a first-time bank, 0 otherwise (fintech lenders and non-banks are excluded) To identify whether the bank previously participated in the SBA programs, we use a combination of code-based and manual check of lender name matching with the SBA 7(a) and 504 loan-level data from 1990-2019.	• PPP loan-level dataset • SBA 7(a) and 504 loan-level dataset (1990-2019)

CD	1 if the lender is a CDFI or CDC, 0 otherwise (fintech lenders and other non-banks are excluded)	• cdfifund.gov • SBA 504 (1990-2019)
Uninsured S&L CU	1 if the lender is not federally insured, 0 otherwise 1 if the lender is a Savings & Loan Association, 0 otherwise 1 if the lender is a Credit Union, 0 otherwise	• FFEIC *Missing if not matched with FFEIC*
I(Rel.) Rel. (N. Loans) Rel. (A. Loan)	1 if the borrower previously borrowed a SBA 7(a) or 504 loan Total number of SBA 7(a) and 504 loans the borrower has Total amount of SBA 7(a) and 504 loans the borrower has (million USD)	SBA 7(a) and 504 loan-level dataset (2009-2019)

Table A2 The List of Fintech Lenders in the First Draw of the PPP Program

Pair #	Servicing Lender	Originating Lender	N. Our	Our/722	N. 722	N. All
1	Cross River Bank	Cross River Bank	2165	26%	8440	324588
2	Cross River Bank Kabbage, Inc.	Kabbage, Inc.	1828	23%	7859	159823
3	Square Capital, LLC	Square Capital, LLC Celtic Bank Corporation	1521	22%	6966	86109
4	WebBank	WebBank	1415	31%	4639	82997
5	First Home Bank Loan Source Incorporated	Loan Source Incorporated some bank[25]	1019	28%	3654	36515
6	Itria Ventures LLC	Itria Ventures LLC	499	4%	12106	197238
7	Customers Bank Readycap Lending, LLC	Readycap Lending, LLC	413	13%	3301	67836
8	FC Marketplace, LLC (dba Funding Circle) Quontic Bank	FC Marketplace, LLC (dba Funding Circle)	187	25%	747	9738
9	Celtic Bank Corporation	Celtic Bank Corporation	155	30%	521	65376
10	Fundbox, Inc.	Fundbox, Inc.	119	23%	511	13454
11	Sunrise Banks, National Association	Sunrise Banks, National Association	69	32%	216	2200
12	BSD Capital, LLC dba Lendistry	BSD Capital, LLC dba Lendistry	67	23%	295	4814
13	Intuit Financing Inc. Quontic Bank	Intuit Financing Inc.	48	33%	145	17792
14	Opportunity Fund Community Development	Opportunity Fund Community Development	16	24%	67	1162
15	FinWise Bank	FinWise Bank	16	35%	46	693

[25] Loan Source shown in the PPP loan-level dataset to have the following 37 originators in the 2020-PPP round: Columbia Community CU, First State Bank, Renaissance Community Loan Fund, Inc., The Bryn Mawr Trust Company, Neighbors FCU, Ascend FCU, FirstBank, BNC National Bank, Pelican State CU, First Reliance Bank, Nano Banc, Pacific Premier Bank, Signature Bank of Georgia, The Hicksville Bank, Florida Capital Bank, National Association, Flagstar Bank, FSB, First Bank of Alabama, Stearns Bank National Association, Sterling National Bank, Bethpage FCU, Marlin Business Bank, KeyPoint CU, BCB Community Bank, Kearny Bank, Five Star Bank, Community Bank and Trust Company, Investors Bank, Peapack-Gladstone Bank, OceanFirst Bank, National Association, Financial Partners CU, Prudential Bank, Gather FCU, Northeast Bank, Southern First Bank, Malvern Bank, National Association, Orange County's CU, Neighborhood National Bank.

A Short Description on the Paycheck Protection Program

The Paycheck Protection Program (PPP) is a Small Business Administration (SBA) loan program established on April 3, 2020 as a temporary addition to the existing 7(a) loan program, in accordance with the Coronavirus Aid, Relief, and Economic Security Act (CARES Act) passed on March 27, 2020. The intent of the PPP is to provide small businesses with funds to maintain payroll costs and cover overheads during the Covid-19 crisis.

The first tranche of the 2020 PPP loans started on April 3, 2020. Until April 16, 2020, the initial allocation of $349 billion authorized by Congress was exhausted. The distribution of the second tranche of the PPP started on April 27 after Congress added additional funding to the program. The initial application deadline for the PPP loans was June 30, 2020 and later extended to August 8, 2020. As of August 8, 2020, in total $525 billion PPP loans were distributed, and $134 billion remained available. In total, $659 billion funds were authorized to the PPP by Public Law 116-147 in 2020.

The Economic Aid to Hard-Hit Small Businesses, Nonprofits, and Venues Act (Economic Aid Act) restarted the issuance of PPP loans in January 2021. The Act added $284 billion funding for PPP loans. The initial deadline of applying for PPP loans is March 31, 2021, later extended to May 31. The 2021 PPP program consists of a first draw for whom have not received a PPP loan before and a second draw for previous PPP recipients in 2020. Moreover, in 2021, the SBA undertook several steps to facilitate lending to minority borrowers, including encourage minority owned lenders to become PPP lenders.

For most industries, the eligibility requirement is either meeting the SBA size standards for small business or less than 500 employees. For the industries with a NAICS code that begins with 72 (Accommodations and Food Services), the business is eligible for the PPP as long as the number of employees is fewer than 500 at each location.

The PPP loans should generally be used for payroll costs and for mortgage interest, rent, utilities, and other worker protection related cost and the interest rate is fixed at 1%. The maturity of the loans issued before June 5, 2020 is two years and five years for loans issued after June 5. The principal of the PPP loan can be partially or fully forgiven conditioning on the loan spending on business maintaining and employee rehiring and maintaining. There is no collateral or personal guarantees requirement. Each loan is 100% guaranteed by the SBA.

Fintech played a crucial role in the distribution of PPP loans. Because of the large amount of loan demand, the goal of providing immediate assistance to borrowers, and the social-distancing requirement during the pandemic, the SBA allowed for a few non-traditional lenders specializing in fintech services to become eligible lenders, in addition to the SBA 7(a) lender, federally insured depository institution or credit union. Examples of fintech lenders in the PPP are Lendio, Paypal, Biz2credit, Kabbage, and Square.

This is the first large scale experiment of including fintech lenders in SBA programs. Most of the fintech companies are not participants in the SBA 7(a) or 504 programs before the Covid-19 crisis and therefore not PPP eligible lenders by default. At the very early stage of the PPP program in 2020, non-depository institutions including fintech companies were not able to operate similarly to depository institutions. On April 8, five days after the beginning of issuing PPP loans, the Federal Reserve Board authorized each regional Federal Reserve Banks to establish the Paycheck Protection Program Liquidity Facility (PPPLP), to provide liquidity to credit market by extending non-recourse credit to PPP lenders and taking PPP loans as collateral. The PPPLF became fully functional on April 16, but only eligible to depository institutions. On April 30, the PPPLP was extended to all PPP lenders approved by the SBA, including fintech companies.

Compare the Racial Group Measures PPP vs Yelp.com

Table A3 The List of Fintech Lenders in the First Draw of the PPP Program

This table reports the relationship between the racial group classification using information from PPP data and Yelp data. Panel A reports the share of each racial group based on information in the PPP loan-level data for each racial group using food type information from yelp.com. Rows indicate the racial group of the restaurant owners in the PPP dataset. Columns indicate the racial group of the restaurant using food type information from yelp.com. For example, the first row of the third column reports that 26.9% of restaurants that are classified as Hispanic based on information from yelp.com are classified as White based on PPP information. Panel B reports the parallel results of shares of Yelp racial groups for each PPP racial groups. Panel C reports the pairwise correlations between PPP race classifications and yelp race classifications. The sample includes all restaurant borrowers which have a valid yelp link and non-missing race and ethnicity information in the PPP dataset.

Panel A: Cross Shares – Compare Yelp with PPP

	Yelp				
	White	Non-White			
PPP		All	Hispanic	African	Asian
White	74.9%	12.2%	26.9%	12.0%	4.7%
Non-White	25.1%	87.8%	73.1%	88.0%	95.3%
Hispanic	3.9%	18.3%	51.9%	1.8%	1.8%
African American	4.0%	5.2%	7.5%	80.1%	0.5%
Asian	13.7%	59.5%	5.9%	1.8%	89.6%
Native American	3.5%	4.8%	7.8%	4.2%	3.4%
Observations	13,327	5,498	1,806	166	3,526

Panel B: Cross Shares – Compare PPP with Yelp

	PPP					
	White	Non-White				
Yelp		All	Hispanic	African American	Asian	Native American
White	93.7%	40.9%	34.2%	65.0%	35.8%	63.6%
Non-White	6.3%	59.1%	65.8%	35.0%	64.2%	36.4%
Hispanic	4.6%	16.2%	61.5%	16.4%	2.1%	19.3%
African American	0.2%	1.8%	0.2%	16.2%	0.1%	1.0%
Asian	1.6%	41.1%	4.1%	2.3%	62.0%	16.2%
Observations	10,657	8,168	1,525	821	5,092	730

Panel C: Pairwise Correlation

	(1) Minority Yelp	(2) African Yelp	(3) Asian Yelp	(4) Hispanic Yelp
Minority PPP	0.58***			
	(0.00)			
African PPP		0.35***		
		(0.00)		
Asian PPP			0.52***	
			(0.00)	
Hispanic PPP				0.68***
				(0.00)
Observations	18,825			

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Proof of Proposition 1

Setting the outside option of borrowers to zero, the equilibrium in the race-biased tech savviness case is given by ($\underline{\gamma_{mf}}, \underline{\gamma_{mb}}, \underline{\gamma_{nmf}}, \underline{\gamma_{nmb}}, p_{mf}, p_{mb}, p_{nmf}, p_{nmb}$) that are determined by

$$M^m \int_{\underline{\gamma_{mf}}}^{\infty} f(x, \mu^m, \sigma^m)dx + M^{nm} \int_{\underline{\gamma_{nmf}}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx = M^f \quad (A.1)$$

$$M^m \int_{\underline{\gamma_{mb}}}^{\underline{\gamma_{mf}}} f(x, \mu^m, \sigma^m)dx + M^{nm} \int_{\underline{\gamma_{nmb}}}^{\underline{\gamma_{nmf}}} f(x, \mu^{nm}, \sigma^{nm})dx = M^b \quad (A.2)$$

$$\underline{\gamma_{mf}}(1 + \theta^m) - p_{mf} = \underline{\gamma_{mf}} - p_{mb} \quad (A.3)$$

$$\underline{\gamma_{nmf}}(1 + \theta^{nm}) - p_{nmf} = \underline{\gamma_{nmf}} - p_{nmb} \quad (A.4)$$

$$\underline{\gamma_{mb}} - p_{mb} = 0 \quad (A.5)$$

$$\underline{\gamma_{nmb}} - p_{nmb} = 0 \quad (A.6)$$

$$p_{mf} = p_{nmf} \quad (A.7)$$

$$p_{mb} = p_{nmb} \quad (A.8)$$

$(A.3)$ to $(A.6)$ are the incentive compatibility constraints for the marginal borrowers in the group of minority-fintech, non-minority-fintech, minority-bank, and non-minority-bank matches respectively.

$(A.7)$ and $(A.8)$ are the lender's incentive compatibility.

$$(A.5) + (A.6) + (A.8) \Rightarrow \underline{\gamma_{mb}} = \underline{\gamma_{nmb}} \; (A.9)$$

$$(A.3) + (A.4) + (A.7) \Rightarrow \underline{\gamma_{mf}}\theta^m = \underline{\gamma_{nmf}}\theta^{nm} \; (A.10)$$

■

Proof of Corollary 1

The double differences in the matching thresholds between the minority-non-minority borrower types and fintech and bank lender types is,

$$(A.9) + (A.10) \Rightarrow \underline{\Delta\Delta} \stackrel{\text{def}}{=} \left(\underline{\gamma_{mf}} - \underline{\gamma_{nmf}}\right) - \left(\underline{\gamma_{mb}} - \underline{\gamma_{nmb}}\right) = \underline{\gamma_{mf}} - \underline{\gamma_{nmf}}$$

$$= \frac{\gamma_{mf}}{\theta^{nm}}(\theta^{nm} - \theta^{m}) < 0 \; if \; \theta^{m} > \theta^{nm}$$

In addition, the double differences in the conditional expectation of the rating level between the minority-non-minority borrower types and fintech and bank lender types is,

$\mathbb{E}(\Delta\Delta|\cdot) \stackrel{\text{def}}{=} \left[\mathbb{E}\left(x\middle|x \geq \underline{\gamma_{mf}}, \mu^{m}, \sigma^{m}\right) - \mathbb{E}\left(x\middle|x \geq \underline{\gamma_{nmf}}, \mu^{nm}, \sigma^{nm}\right)\right] -$

$\left[\mathbb{E}\left(x\middle|\underline{\gamma_{mb}} \leq x < \underline{\gamma_{mf}}, \mu^{m}, \sigma^{m}\right) - \mathbb{E}\left(x\middle|\underline{\gamma_{nmb}} \leq x < \underline{\gamma_{nmf}}, \mu^{nm}, \sigma^{nm}\right)\right]$

$$= \left[\mu^{m} + \sigma^{m}\frac{\varphi\left(\frac{\underline{\gamma_{mf}} - \mu^{m}}{\sigma^{m}}\right)}{1-\Phi\left(\frac{\underline{\gamma_{mf}} - \mu^{m}}{\sigma^{m}}\right)} - \sigma^{nm}\frac{\varphi\left(\frac{\underline{\gamma_{nmf}} - \mu^{nm}}{\sigma^{nm}}\right)}{1-\Phi\left(\frac{\underline{\gamma_{nmf}} - \mu^{nm}}{\sigma^{nm}}\right)} - \mu^{nm}\right] - \left[\mu^{m} + \sigma^{m}\frac{\varphi\left(\frac{\underline{\gamma_{mb}} - \mu^{m}}{\sigma^{m}}\right) - \sigma^{m}\varphi\left(\frac{\underline{\gamma_{mf}} - \mu^{m}}{\sigma^{m}}\right)}{\Phi\left(\frac{\underline{\gamma_{mf}} - \mu^{m}}{\sigma^{m}}\right) - \Phi\left(\frac{\underline{\gamma_{mb}} - \mu^{m}}{\sigma^{m}}\right)} - \right.$$

$$\left. \sigma^{nm}\frac{\varphi\left(\frac{\underline{\gamma_{nmb}} - \mu^{nm}}{\sigma^{nm}}\right) - \varphi\left(\frac{\underline{\gamma_{nmf}} - \mu^{nm}}{\sigma^{nm}}\right)}{\Phi\left(\frac{\underline{\gamma_{nmf}} - \mu^{nm}}{\sigma^{nm}}\right) - \Phi\left(\frac{\underline{\gamma_{nmb}} - \mu^{nm}}{\sigma^{nm}}\right)} - \mu^{nm}\right]$$

$$= \sigma^{m}\left[\frac{\varphi\left(\frac{\underline{\gamma_{mf}} - \mu^{m}}{\sigma^{m}}\right)}{1-\Phi\left(\frac{\underline{\gamma_{mf}} - \mu^{m}}{\sigma^{m}}\right)} - \frac{\varphi\left(\frac{\underline{\gamma_{mb}} - \mu^{m}}{\sigma^{m}}\right) - \varphi\left(\frac{\underline{\gamma_{mf}} - \mu^{m}}{\sigma^{m}}\right)}{\Phi\left(\frac{\underline{\gamma_{mf}} - \mu^{m}}{\sigma^{m}}\right) - \Phi\left(\frac{\underline{\gamma_{mb}} - \mu^{m}}{\sigma^{m}}\right)}\right] - \sigma^{nm}\left[\frac{\varphi\left(\frac{\underline{\gamma_{nmf}} - \mu^{nm}}{\sigma^{nm}}\right)}{1-\Phi\left(\frac{\underline{\gamma_{nmf}} - \mu^{nm}}{\sigma^{nm}}\right)} - \frac{\varphi\left(\frac{\underline{\gamma_{nmb}} - \mu^{nm}}{\sigma^{nm}}\right) - \varphi\left(\frac{\underline{\gamma_{nmf}} - \mu^{nm}}{\sigma^{nm}}\right)}{\Phi\left(\frac{\underline{\gamma_{nmf}} - \mu^{nm}}{\sigma^{nm}}\right) - \Phi\left(\frac{\underline{\gamma_{nmb}} - \mu^{nm}}{\sigma^{nm}}\right)}\right] \quad (A.11)$$

Where $\varphi(\cdot)$ and $\Phi(\cdot)$ are the density and cumulative distribution function of the standard normal distribution.

Suppose the underlying distribution is the same for minority and non-minority groups, i.e., $\mu^{m} = \mu^{nm} = \mu$ and $\sigma^{m} = \sigma^{nm} = \sigma$, combining with $(A.9)$ $\underline{\gamma_{mb}} = \underline{\gamma_{nmb}} = \sigma\tilde{\gamma} + \mu$, (A.11) becomes,

$\sigma\left(G\left(\frac{\underline{\gamma_{mf}} - \mu}{\sigma}\right) - G\left(\frac{\underline{\gamma_{nmf}} - \mu}{\sigma}\right)\right)$, where $G(x) = \frac{\varphi(x)}{1-\Phi(x)} - \frac{\varphi(\tilde{\gamma}) - \varphi(x)}{\Phi(x) - \Phi(\tilde{\gamma})}$.

Using the symmetricity of normal distribution, $G(x) = \frac{\varphi(x)}{1-\Phi(x)} - \frac{\varphi(\tilde{\gamma}) - \varphi(x)}{\Phi(x) - \Phi(\tilde{\gamma})} = \frac{\varphi(x)}{\Phi(-x)} + \frac{\varphi(x) - \varphi(\tilde{\gamma})}{\Phi(x) - \Phi(\tilde{\gamma})}$

■

Online Appendices for "Can Fintech Benefit Minority-owned Small Businesses? Evidence from the Paycheck Protection Program"

Appendix A Additional Figures

Appendix B Additional Tables

Appendix C Data Construction

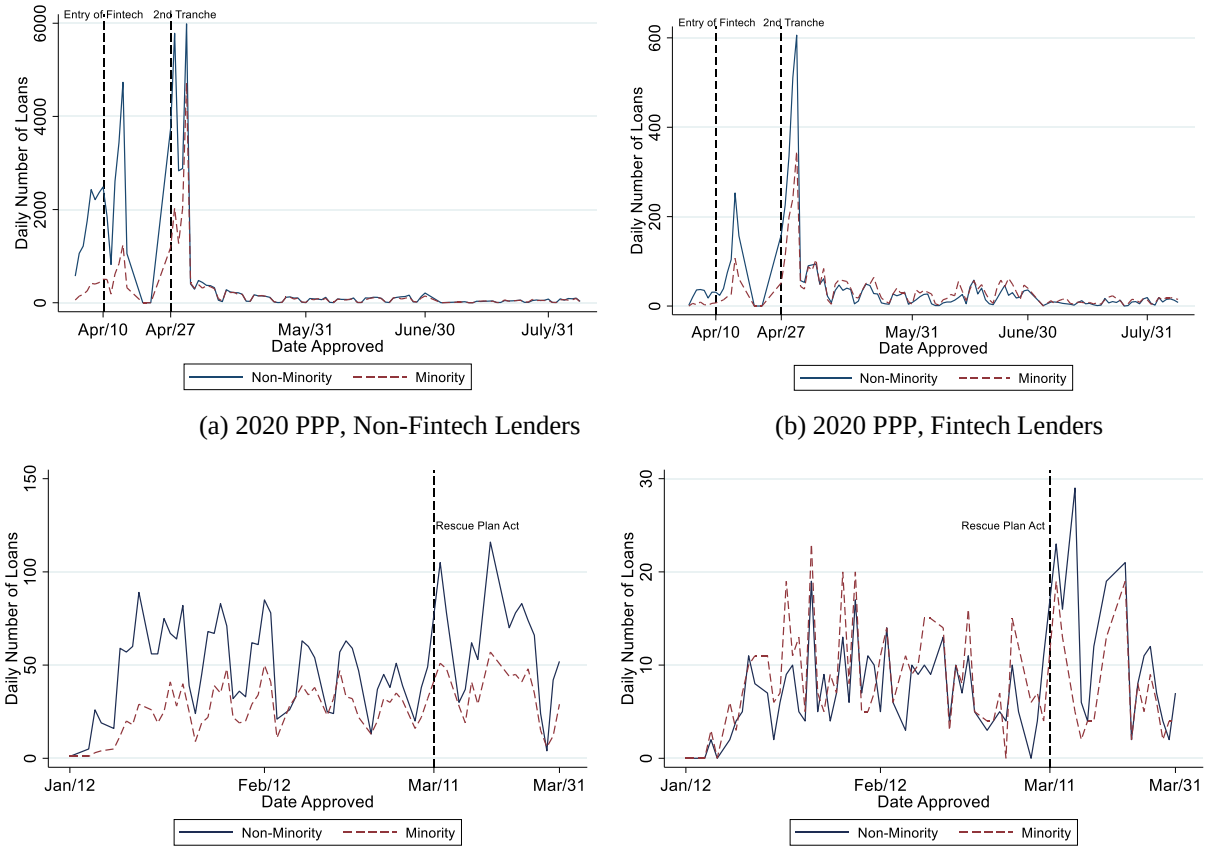
Appendix C1 Identify Fintech Lenders

Appendix C2 Lenders Classifications and Matching with FFIEC

Appendix C3 Linking a Business Entity Participated in the Paycheck Protection Program with a Restaurant on Yelp.com

Appendix D Theoretical Matching Model Analysis

Appendix A Additional Figures



(a) 2020 PPP, Non-Fintech Lenders

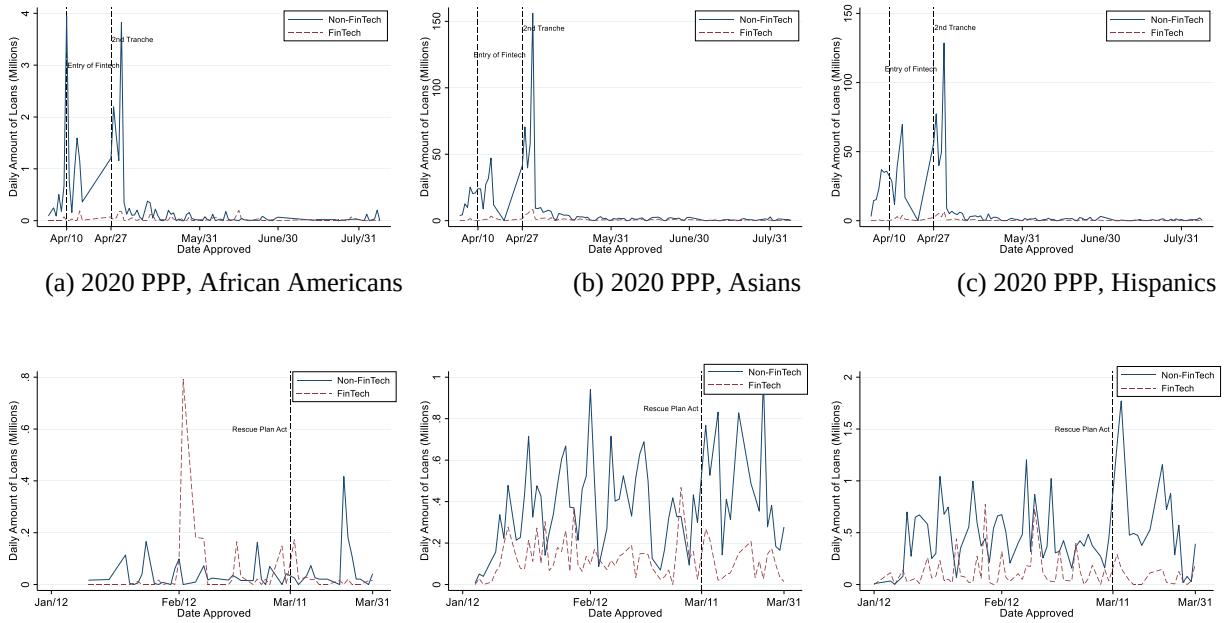
(b) 2020 PPP, Fintech Lenders

(c) 2021 PPP, Non-Fintech Lenders

(d) 2021 PPP, Fintech Lenders

Figure A1 Differences between Minority and Non-Minority Borrowers (N. Loans)

This figure plots the daily number of PPP loans processed by non-fintech (panel (a)) and fintech (panel (b)) lenders and received by minority and non-minority borrowers in the 2020 PPP during April 3, 2020 and August 8, 2020 for our restaurant sample of analysis. Similar plots for the 2021 program during January 12, 2021 and March 31, 2021 are in panel (c) for non-fintech lenders and panel (d) for fintech lenders. y-axis is the daily number of loans processed by each type of lenders to each borrower group, and x-axis is loan approval date. The blue solid line is for the non-minority group and the red dashed line is for the minority group. In panels (a) and (b), the first vertical dashed line indicates the time of the entry of fintech lenders on April 10, 2020 and the second vertical dashed line indicates the time of the beginning of the second tranche of the 2020 PPP on April 27. In panels (c) and (d), the vertical dashed line indicates the time of American Rescue Plan Act of 2021 enacted on March 11, 2021.

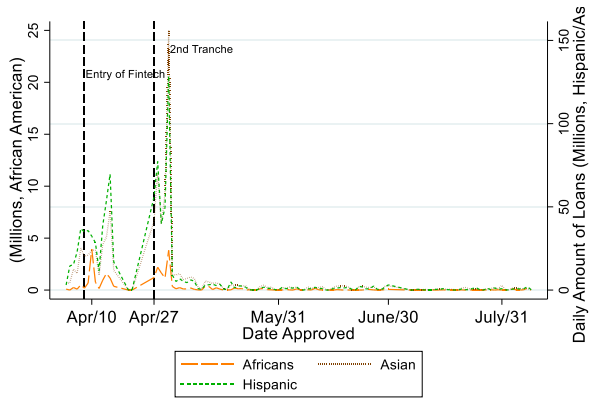


(a) 2020 PPP, African Americans (b) 2020 PPP, Asians (c) 2020 PPP, Hispanics

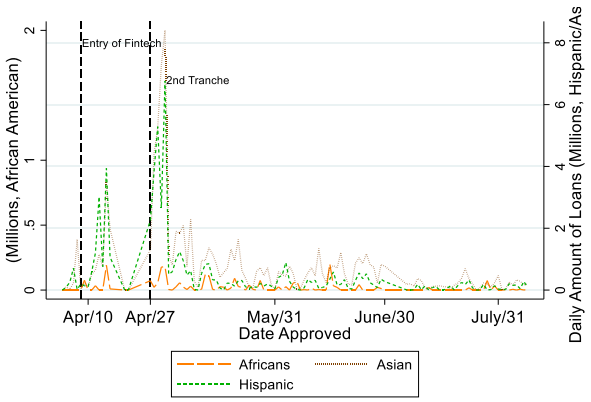
(d) 2021 PPP, African Americans (e) 2021 PPP, Asians (f) 2021 PPP, Hispanics

Figure A2 Differences between Minority and Non-Minority Borrowers Across Racial Groups

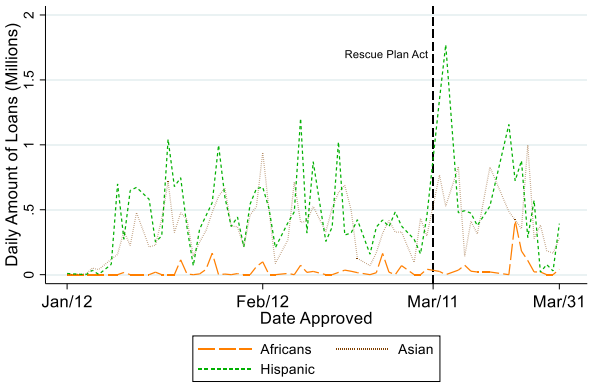
This figure plots the daily amount (USD millions) of PPP loans received by African American (panel (a)), Asian (panel (b)), and Hispanic (panel (c)) borrowers in the 2020 PPP during April 3, 2020 and August 8, 2020 for our restaurant sample of analysis. Similar plots for the 2021 program during January 12, 2021 and March 31, 2021 are in panels (e) to (g) for African American, Asian, and Hispanic borrowers respectively. y-axis is the daily amount of loans processed by each type of lenders to each borrower group, and x-axis is loan approval date. The blue solid line is for the non-minority group and the red dashed line is for the minority group. In panels (a) to (c), the first vertical dashed line indicates the time of the entry of fintech lenders on April 10, 2020 and the second vertical dashed line indicates the time of the beginning of the second tranche of the 2020 PPP on April 27. In panels (d) to (f), the vertical dashed line indicates the time of American Rescue Plan Act of 2021 enacted on March 11, 2021.



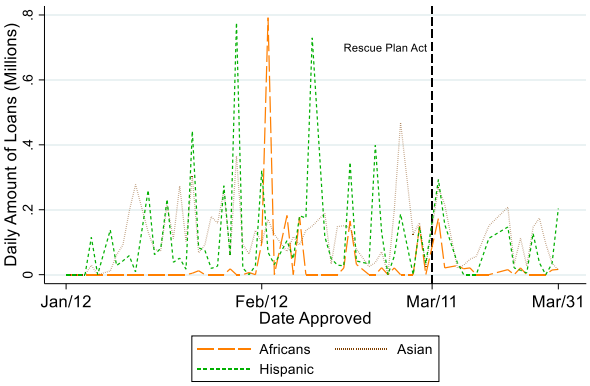
(a) 2020 PPP, Non-Fintech Lenders



(b) 2020 PPP, Fintech Lenders



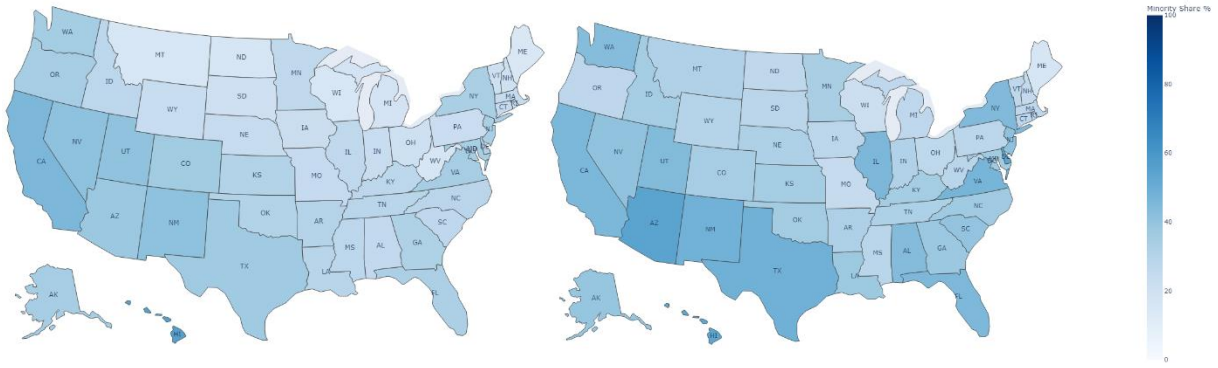
(c) 2021 PPP, Non-Fintech Lenders



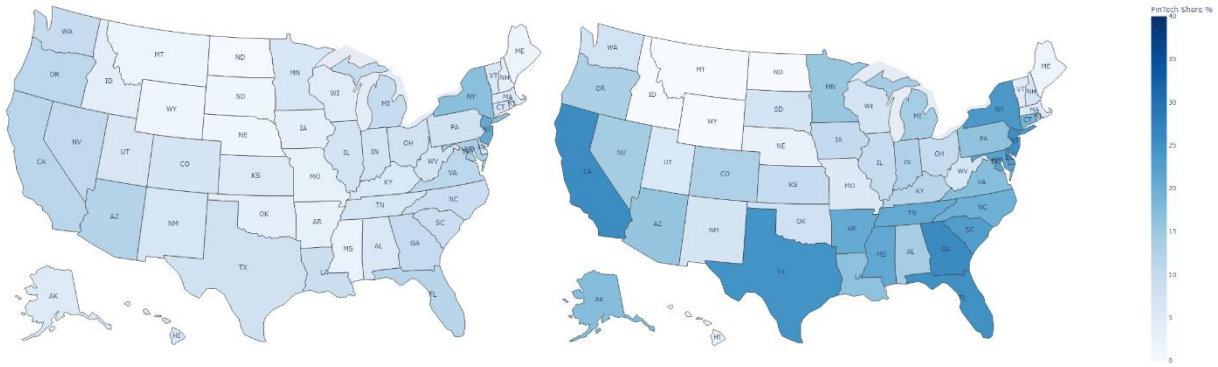
(d) 2021 PPP, Fintech Lenders

Figure A3

Amount of loans, across racial groups. For panels (a) and (b), the axis for African Americans is rescaled and shown on the right for demonstration purpose.



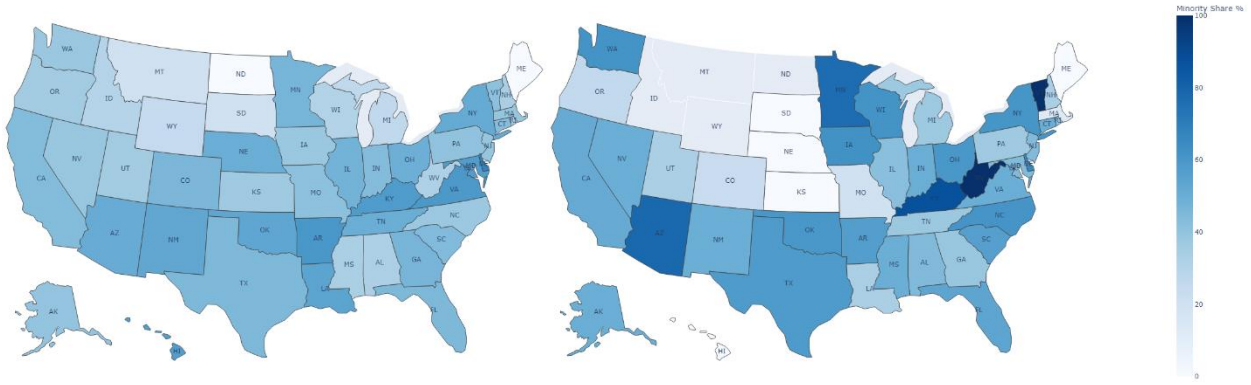
(a) Minority Share (Total) in 2020 PPP (b) Minority Share (Total) in 2021 PPP



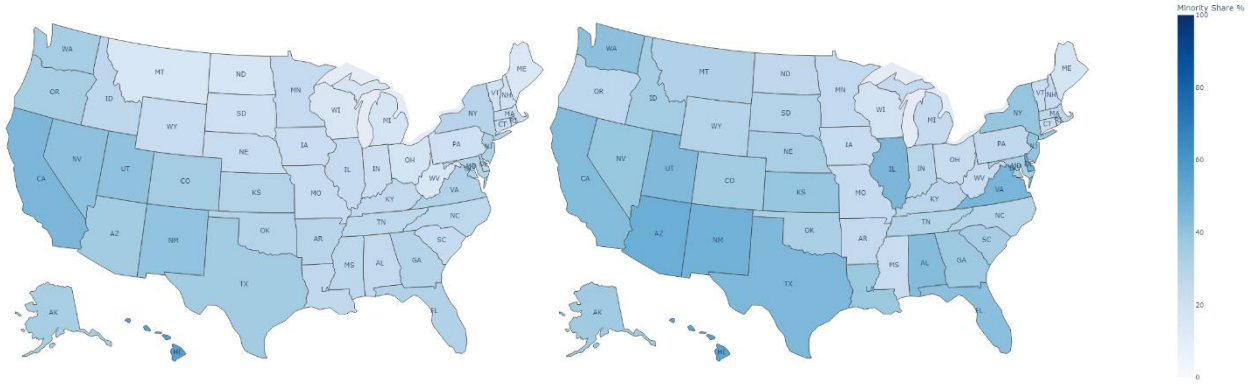
(c) Fintech Share in 2020 PPP (d) Fintech Share in 2021 PPP

Figure A4 Percentage of Loans Distributed to Minorities (Amount)

This figure plots the share of number of loans distributed to minority borrowers in the 2020 PPP program (panel (a)) and in the 2021 PPP program (panel (b)), and the share of loan amounts (USD) processed by fintech lenders in the 2020 PPP program (panel (c)) and the 2021 PPP program (panel (d)), based on our restaurant sample of analysis. The *Minority Shares* ranges from 0% (lightest blue) to 100% (darkest blue).The *FinTech Shares* range from 0% (lightest blue) to 40% (darkest blue).



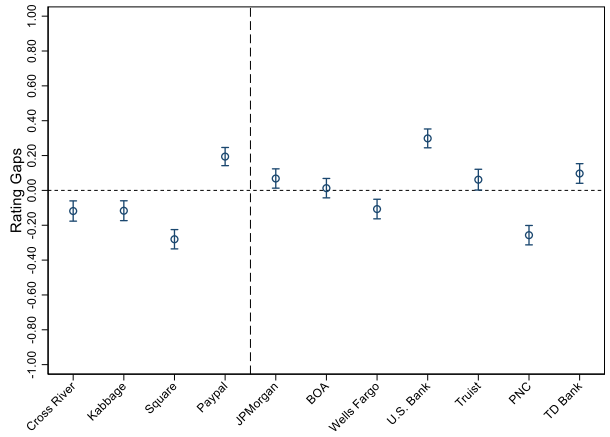
(a) Minority Share (Fintech) in 2020 PPP (b) Minority Share (Fintech) in 2021 PPP



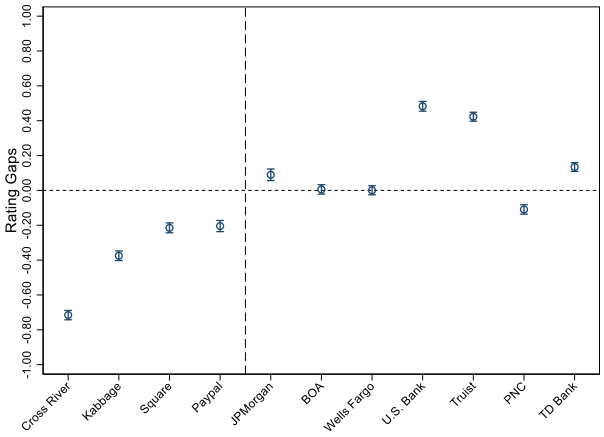
(c) Minority Share (Non-Fintech) in 2020 PPP (d) Minority Share (Non-Fintech) in 2021 PPP

Figure A5 Percentage of Loans Distributed to Minorities
Fintech vs. Non-Fintech (N. of Loans)

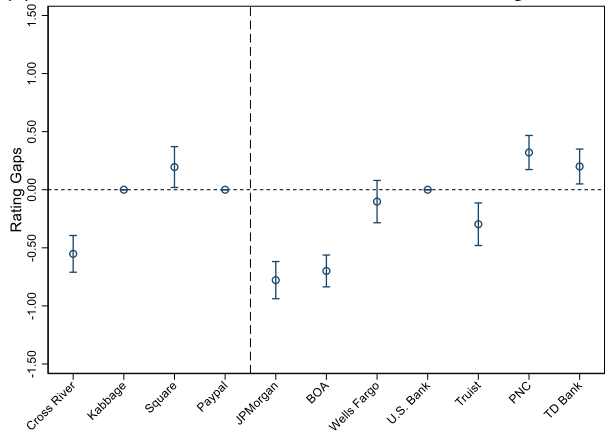
This figure plots the share of loan number processed by fintech lenders (panel (a)) and non-fintech lenders (panel (c)) in the 2020 PPP program and in the 2021 PPP program (panel (b), (d)) respectively, based on our restaurant sample of analysis. The *Minority Shares* range from 0% (lightest blue) to 100% (darkest blue).



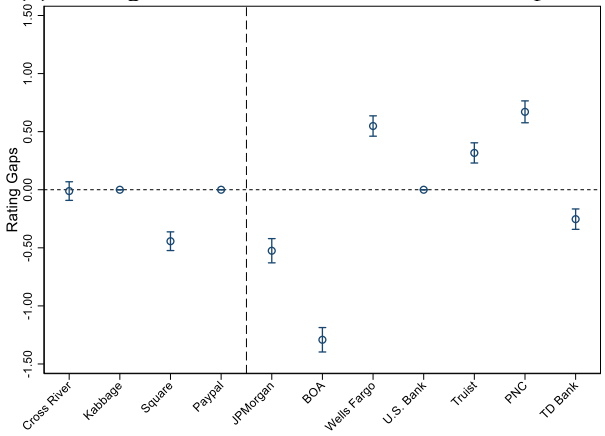
(a) Before Covid-19 Period, 2020 PPP Recipients



(b) During Covid-19 Period, 2020 PPP Recipients

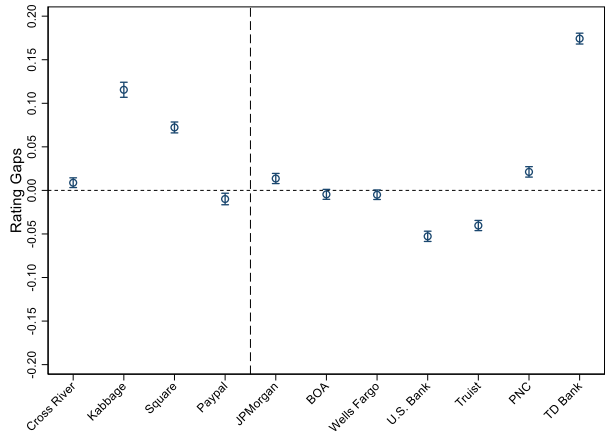


(c) Before Covid-19 Period, 2021 PPP Recipients

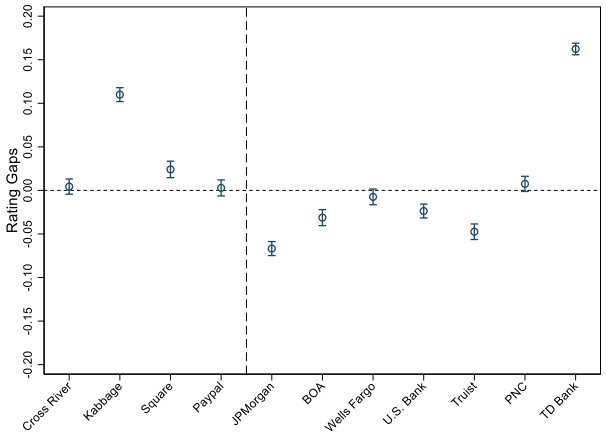


(d) During Covid-19 Period, 2021 PPP Recipients

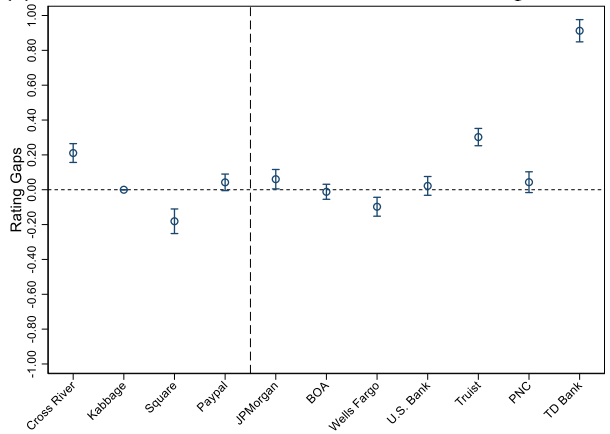
Figure A6 Minority-Non-Minority Rating Gap (African Group)
Fintech vs. Non-Fintech



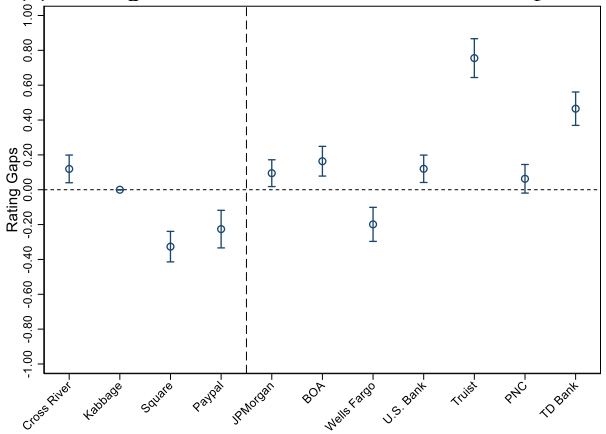
(a) Before Covid-19 Period, 2020 PPP Recipients



(b) During Covid-19 Period, 2020 PPP Recipients



(c) Before Covid-19 Period, 2021 PPP Recipients



(d) During Covid-19 Period, 2021 PPP Recipients

Figure A7 Minority-Non-Minority Rating Gap (Hispanic Group)
Fintech vs. Non-Fintech

Appendix B Additional Tables

Table B1 Compare Our Sample with the Sample in Erel and Liebersohn (2020)

The difference between our sample and the EL Sample can be attributed to 1) we exclude borrowers in state of PR, and non-profit organizations; 2) We adjust the lender identity to either the originating or the servicing lender is the fintech lender. For example, because Celtic Bank Corporation is also the originator of loans by Square Capital in addition to Square Capital itself as the originator, we assign those loans where the originating and servicing lender pair is Celtic Bank Corporation and Square Capital as with Square Capital. Adding the number of loans by both Celtic Bank Corporation and Square Capital gives a close number to the EL sample. Taking these modification into account, our sample is comparable with the EL sample.

	Our Sample		EL Sample	
	PPP 2020	PPP 2021	PPP 2020	Our/EL
Cross River Bank	185207	139381	198738	93%
Kabbage, Inc.	159823		196402	81%
Square Capital, LLC	75096	11013	0	
WebBank	74620	8377	76578	97%
Celtic Bank Corporation	65376		147317	44%
Readycap Lending, LLC	34232	33604	34261	100%
Loan Source Incorporated	33050	3594	0	
Intuit Financing Inc.	17792		19086	93%
Fundbox, Inc.	13454		14281	94%
FC Marketplace, LLC (dba Funding Circle)	5963	3775	6235	96%
BSD Capital, LLC dba Lendistry	3504	1310	4076	86%
Itria Ventures LLC	3028	194210	3556	85%
Sunrise Banks, National Association	1655	545	0	
Opportunity Fund Community Development	978	184	990	99%
FinWise Bank	693		699	99%

Table B2 Restaurant Ratings (Motivation Facts)

This table reports the regression results examining the relationship between restaurant ratings and fintech/racial group indicators. The dependent variable is the *Rating Stars*, within the range of 0 to 5, based on the customer reviews from yelp.com. The year of the PPP program (2020 or 2021) is indicated in the column heads. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. *African*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. In addition to the variables reported in the table, we also control for city × month fixed effects, business type fixed effects, and eating policy dummies for options of delivery, takeout, reservations, and outdoor seating. Detailed variable definitions are in Appendix-Table A1. Standard errors are clustered at restaurant level. The regression is based on our linked restaurant loan-level panel sample where rating is calculated as the average for each month. The sample period is April 2018 to March 2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Rating Stars			
Sample	2020 PPP	2021 PPP	2020 PPP	2021 PPP
	(1)	(2)	(3)	(4)
I(Fintech)	0.02***	-0.04		
	(0.01)	(0.04)		
I(African)			0.10***	0.10
			(0.03)	(0.10)
I(Asian)			-0.07***	-0.08**
			(0.01)	(0.03)
I(Hispanic)			-0.09***	-0.10***
			(0.01)	(0.04)
Employment	-0.11***	-0.34**	-0.12***	-0.36**
	(0.01)	(0.15)	(0.01)	(0.15)
I(Franchise)	-0.89***	-0.81***	-0.91***	-0.83***
	(0.01)	(0.07)	(0.01)	(0.07)
City × Monthly FEs	Yes	Yes	Yes	Yes
Business Type FEs	Yes	Yes	Yes	Yes
Eating Policy Controls	Yes	Yes	Yes	Yes
Observations	1409729	43981	1409729	43981
Adjusted R^2	0.069	0.049	0.070	0.050

Table B3 Restaurant Ratings (Robustness – Combining Minorities into One Group)

This table reports the regression results of the robustness check of Table 3 by combining *African*, *Asian*, and *Hispanic* indicators into one minority indictor. As effects vary across different minority groups, we report the results of the specifications using decomposed group indicators in the main text. The regressions examine the difference in restaurant ratings between minority and non-minority borrowers who are matched with fintech and non-fintech lenders. The dependent variable is the *Rating Stars*, within the range of 0 to 5, based on the customer reviews from yelp.com. In pane A and B, we report results on the 2020 PPP and 2021 PPP, respectively. *African*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. Matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, business type (aggregated), food price range, and with a difference of at most five employees in employment size. Other Controls are *Employment*, *I*(Franchise), business type fixed effects, and eating policy dummies for options of delivery, takeout, reservations, and outdoor seating. Fixed effects are indicated in table. Detailed variable definitions are in Appendix-Table A1. The regression is based on our linked restaurant loan-level panel sample where rating is calculated as the average for each month. The time period for the "Before Covid-19" sample is from April 2018 to March 2020, and the "During Covid-19" sample is from April 2020 to March 2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority) × *I*(Fintech)	-0.06***	-0.06***	-0.06***	-0.06***	-0.04**	-0.02	-0.05**	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
I(Fintech)	0.05***	0.06***	0.05***	0.06***	0.05***	0.04**	0.04***	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Minority)	-0.08***	-0.07***	-0.09***	-0.08***	-0.06***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	1032002	974781	959322	902934	464639	434948	432598	403363
Adjusted R^2	0.046	0.067	0.043	0.064	0.051	0.072	0.048	0.069

Panel B: 2021 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority) × *I*(Fintech)	0.04	0.08	0.04	0.09	-0.08	-0.10	-0.07	-0.08
	(0.05)	(0.08)	(0.05)	(0.08)	(0.06)	(0.09)	(0.06)	(0.09)
I(Fintech)	-0.06*	-0.07	-0.07*	-0.08	-0.06	-0.02	-0.07	-0.03
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
I(Minority)	-0.12***	-0.10***	-0.13***	-0.10***	-0.09***	-0.04	-0.09***	-0.04
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.03)	(0.04)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	51844	29256	50102	28211	26491	14723	25476	14095
Adjusted R^2	0.039	0.048	0.039	0.049	0.039	0.048	0.038	0.045

Table B4 Restaurant Ratings (Extensions – Effects from Non-Fintech or Fintech)

This table reports the regression results of the extensions of Table 3 by separating the sample into fintech and non-fintech borrowers. This can help us to better understand where the gap comes from. The regressions examine the difference in restaurant ratings between minority and non-minority borrowers. The dependent variable is the *Rating Stars*, within the range of 0 to 5, based on the customer reviews from yelp.com. In pane A and B, we report results on the 2020 PPP for the non-fintech and fintech borrowers, and in panel C and D on the 2021 PPP, respectively. *African*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. Matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, business type (aggregated), food price range, and with a difference of at most five employees in employment size. Other Controls are *Employment*, *I*(Franchise), business type fixed effects, and eating policy dummies for options of delivery, takeout, reservations, and outdoor seating. Fixed effects are indicated in table. Detailed variable definitions are in Appendix-Table A1. The regression is based on our linked restaurant loan-level panel sample where rating is calculated as the average for each month. The time period for the "Before Covid-19" sample is from April 2018 to March 2020, and the "During Covid-19" sample is from April 2020 to March 2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw, Non-Fintech-Backed Restaurants

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African)	0.12***	0.15***	0.11***	0.14***	0.05	0.06	0.04	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
I(Asian)	-0.09***	-0.07***	-0.09***	-0.08***	-0.03***	-0.03***	-0.04***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Hispanic)	-0.09***	-0.09***	-0.09***	-0.09***	-0.11***	-0.11***	-0.11***	-0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	937462	879943	867060	810503	421431	391707	390451	361284
Adjusted R^2	0.047	0.069	0.044	0.066	0.052	0.073	0.049	0.069

Panel B: 2020 PPP First Draw, Fintech-Backed Restaurants

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African)	-0.00	0.04	-0.01	0.04	-0.23**	-0.12	-0.24**	-0.13
	(0.07)	(0.07)	(0.07)	(0.07)	(0.10)	(0.11)	(0.10)	(0.11)
I(Asian)	-0.17***	-0.16***	-0.18***	-0.16***	-0.11***	-0.07**	-0.11***	-0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
I(Hispanic)	-0.09***	-0.08***	-0.10***	-0.08**	-0.13***	-0.11***	-0.14***	-0.12***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	94540	71809	92262	70006	43208	31725	42147	30882
Adjusted R^2	0.038	0.068	0.037	0.066	0.051	0.076	0.048	0.075

Table B4 Restaurant Ratings (Extensions – Effects from Non-Fintech or Fintech) (Cont.)

Panel C: 2021 PPP First Draw, Non-Fintech-Backed Restaurants								
Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African)	0.15	0.30**	0.14	0.28**	-0.05	0.00	-0.05	-0.00
	(0.11)	(0.13)	(0.11)	(0.13)	(0.11)	(0.12)	(0.11)	(0.12)
I(Asian)	-0.13***	-0.14***	-0.15***	-0.15***	-0.04	0.00	-0.05	0.00
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.05)
I(Hispanic)	-0.13***	-0.10**	-0.12***	-0.10*	-0.16***	-0.10*	-0.15***	-0.09
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	42470	22148	40902	21290	21742	11207	20817	10676
Adjusted R^2	0.042	0.053	0.042	0.054	0.041	0.051	0.039	0.047
Panel D: 2021 PPP First Draw, Fintech-Backed Restaurants								
Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African)	0.02	-0.01	0.02	-0.00	-0.22	-0.46*	-0.22	-0.49*
	(0.12)	(0.25)	(0.12)	(0.25)	(0.14)	(0.27)	(0.14)	(0.27)
I(Asian)	-0.09	-0.05	-0.08	-0.04	-0.03	-0.06	-0.03	-0.05
	(0.06)	(0.13)	(0.06)	(0.13)	(0.07)	(0.13)	(0.07)	(0.13)
I(Hispanic)	-0.04	0.04	-0.04	0.05	-0.33***	-0.43***	-0.33***	-0.42***
	(0.07)	(0.14)	(0.07)	(0.14)	(0.08)	(0.15)	(0.08)	(0.16)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	9373	3333	9199	3308	4749	1589	4659	1576
Adjusted R^2	0.029	0.045	0.028	0.042	0.040	0.029	0.041	0.022

Table B5 Previous Lending Relationships (Full Sample)

This table reports the regression results examining the difference in previous lending relationships between minority and non-minority borrowers for the full sample. In pane A and B, we report results on the 2020 PPP and 2021 PPP, respectively. The dependent variable in columns (1) and (2) is a dummy variable that is defined to be 1 if the borrower has borrowed SBA 7(a) or 504 loans during the period of 2009-2019. In columns (3) and (4) ((5) and (6)), the dependent variable is the total number (million amount) of previously borrowed SBA 7(a) or 504 loans during 2009-2019. Loan amount is winsorized at the 1% and 99% cuts. *African*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. In addition to the variables reported in the table, we also control for city and business type fixed effects. Detailed variable definitions are in Appendix-Table A1. For demonstration purpose, all dependent variables are multiplied by 100 and *Employment* is divided by 100. Standard errors are clustered at city level and are reported in the parentheses. The regression is based on our linked restaurant loan-level cross-sectional sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*I*(Rel.)	*I*(Rel.)	Rel. (N. Loans)	Rel. (N. Loans)	Rel. (A. Loan)	Rel. (A. Loan)
I(African)	-0.92	-1.02	-1.12	-1.31	-0.20	-0.35
	(0.66)	(0.68)	(1.07)	(1.12)	(0.33)	(0.33)
I(Asian)	-0.78***	-1.04***	-1.18***	-1.48***	-0.11	-0.29***
	(0.16)	(0.18)	(0.22)	(0.25)	(0.08)	(0.10)
I(Hispanic)	-1.05***	-0.98***	-1.54***	-1.37***	-0.25***	-0.32***
	(0.15)	(0.17)	(0.20)	(0.22)	(0.09)	(0.09)
Employment	0.63***	0.52**	1.46***	1.28***	1.35***	1.32***
	(0.20)	(0.21)	(0.38)	(0.40)	(0.18)	(0.18)
I(Franchise)	3.84***	3.80***	4.21***	4.13***	2.19***	2.12***
	(0.28)	(0.30)	(0.37)	(0.40)	(0.17)	(0.18)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	92556	88873	92556	88873	92556	88873
Adjusted R^2	0.011	0.008	0.008	0.004	0.010	-0.013

Panel B: 2021 PPP First Draw

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*I*(Rel.)	*I*(Rel.)	Rel. (N. Loans)	Rel. (N. Loans)	Rel. (A. Loan)	Rel. (A. Loan)
I(African)	0.72	1.89	0.38	1.53	-0.24	-0.14
	(1.69)	(2.31)	(1.70)	(2.37)	(0.20)	(0.27)
I(Asian)	-0.45	-0.05	-0.71	-0.03	-0.23**	-0.35*
	(0.40)	(0.56)	(0.46)	(0.64)	(0.10)	(0.21)
I(Hispanic)	-0.65	0.05	-0.89*	0.12	-0.20	-0.08
	(0.44)	(0.66)	(0.52)	(0.76)	(0.16)	(0.22)
Employment	2.51	2.03	2.65	2.46	1.51**	1.69*
	(2.05)	(1.61)	(2.17)	(2.11)	(0.72)	(0.99)
I(Franchise)	1.45	1.47	1.68	2.10	0.39	0.58
	(0.93)	(1.19)	(1.17)	(1.60)	(0.32)	(0.47)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	6266	4150	6266	4150	6266	4150
Adjusted R^2	0.005	0.013	0.005	0.041	0.003	-0.094

Table B6 Business Capital (Full Sample)

This table reports the regression results examining the impact of business capital on the fintech-minority double difference in restaurant ratings for the full sample. The dependent variable is the *Rating Stars*, within the range of 0 to 5, based on the customer reviews from yelp.com. Business capital (*BC*) is proxied by the total number of ratings/100 in the entire period of our analysis (from April 2018 to March 2021) and winsorized at the 99% cuts. Sample periods are indicated in the column heads. The time period for the "Before Covid-19" sample is from April 2018 to March 2020, and the "During Covid-19" sample is from April 2020 to March 2021. In addition to the variables reported in the table, we also control for city × month (or month) fixed effects, and other control variables (business type fixed effects and eating policy dummies). Detailed variable definitions are in Appendix-Table A1. *Employment* is divided by 100 for demonstration purpose. Standard errors are clustered at restaurant level and are reported in the parentheses. The regression is based on our linked restaurant loan-level panel sample where rating is calculated as the average for each month. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(FT) × BC	0.06	0.07	0.03	0.02	-0.01	-0.08	-0.01	0.00
	(0.04)	(0.04)	(0.13)	(0.11)	(0.09)	(0.12)	(0.08)	(0.12)
I(Asia.) × *I*(FT) × BC	0.10***	0.09***	0.07***	0.07***	0.23***	0.28***	0.11**	0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.05)	(0.04)	(0.05)
I(Hisp.) × *I*(FT) × BC	0.12***	0.11***	0.09***	0.08***	0.05	-0.01	-0.09	-0.19*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.09)	(0.08)	(0.11)
I(FT)	-0.02**	-0.01	-0.01	-0.01	-0.10***	-0.09**	-0.11***	-0.09*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
I(African)	0.11***	0.13***	0.01	0.03	0.12	0.25**	-0.08	-0.08
	(0.03)	(0.03)	(0.04)	(0.04)	(0.10)	(0.12)	(0.10)	(0.12)
I(Asian)	-0.10***	-0.09***	-0.04***	-0.04***	-0.16***	-0.15***	-0.05**	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.10***	-0.09***	-0.12***	-0.12***	-0.12***	-0.07	-0.19***	-0.13**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
Employment	-0.12***	-0.12***	-0.11***	-0.12***	-0.35***	-0.33**	-0.38***	-0.43**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.11)	(0.15)	(0.10)	(0.19)
I(Franchise)	-0.89***	-0.87***	-1.06***	-1.02***	-0.91***	-0.84***	-0.92***	-0.82***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)	(0.08)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	1032002	974781	464639	434948	51844	29256	26491	14723
Adjusted R^2	0.047	0.067	0.052	0.072	0.041	0.052	0.041	0.050

Table B7 Relative Geographic Lending Scope (Full Sample)

This table reports the regression results examining the impact of geographic lending scope on the fintech-minority double difference in restaurant ratings for the full sample. The dependent variable is the *Rating Stars*, within the range of 0 to 5, based on the customer reviews from yelp.com. Relative geographic lending scope (GS_r) is calculated as the total number of zip codes divided by the total number of cities that the lender covers in the entire PPP loan sample. CDFIs and CDCs are excluded because their lending scope may be restricted to certain communities. Sample periods are indicated in the column heads. "Before Covid-19" refers to the time period from April 2018 to March 2020, and "During Covid-19" refers to April 2020 to March 2021. In addition to the variables reported in the table, we also control for city × month (or month) fixed effects, and other control variables (business type fixed effects and eating policy dummies). Detailed variable definitions are in Appendix-Table A1. *Employment* is divided by 100 for demonstration purpose. Standard errors are clustered at restaurant level and are reported in the parentheses. The regression is based on our linked restaurant loan-level panel sample where rating is calculated as the average for each month. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.)×*I*(FT)×GS_r	-0.08	-0.06	-0.16**	-0.15**	-0.08	-0.21	-0.08	-0.18
	(0.05)	(0.05)	(0.07)	(0.07)	(0.11)	(0.14)	(0.12)	(0.14)
I(Asian)×*I*(FT)×GS_r	-0.06***	-0.06***	-0.04***	-0.03*	0.01	0.05	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(Hisp.)×*I*(FT)×GS_r	-0.01	0.01	-0.01	0.00	0.05	0.07	-0.12**	-0.19**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.07)	(0.06)	(0.09)
I(FT)	0.05***	0.06***	0.05***	0.04***	-0.06	-0.06	-0.05	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(African)	0.12***	0.15***	0.04	0.06	0.15	0.31**	-0.07	-0.02
	(0.03)	(0.03)	(0.04)	(0.04)	(0.11)	(0.13)	(0.12)	(0.14)
I(Asian)	-0.08***	-0.07***	-0.03***	-0.03***	-0.13***	-0.13***	-0.03	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.09***	-0.09***	-0.11***	-0.11***	-0.13***	-0.09*	-0.16***	-0.10*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.04)	(0.06)
Employment	-0.12***	-0.12***	-0.11***	-0.11***	-0.35***	-0.34**	-0.39***	-0.43**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.11)	(0.16)	(0.10)	(0.19)
I(Franchise)	-0.89***	-0.87***	-1.06***	-1.02***	-0.91***	-0.82***	-0.91***	-0.81***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.06)	(0.08)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	1025335	968144	461493	431821	51114	28634	26025	14342
Adjusted R^2	0.047	0.067	0.052	0.072	0.039	0.049	0.041	0.050

Table B8 Geographic Lending Scope – City vs Zip-Code Level (Matched Sample)

This table reports the regression results examining the different impacts of city- and zip-code-level geographic lending scope on the fintech-minority double difference in restaurant ratings for the matched sample. The dependent variable is the *Rating Stars*, within the range of 0 to 5, based on the customer reviews from yelp.com. Geographic lending scope at the zip code/city level (GS_{zip}/GS_{city}) is calculated as the total number of zip codes/cities that the lender covers in the entire PPP loan sample, divided by 10,000/1000 for demonstration purpose, and winsorized at the 99% cuts. CDFIs and CDCs are excluded because their lending scope may be restricted to certain communities. Credit unions are excluded for regression tractable reasons. Sample periods are indicated in the column heads. "Before Covid-19" refers to the time period from April 2018 to March 2020, and "During Covid-19" refers to April 2020 to March 2021. Matched sample construction and control variables are the same as before. Detailed variable definitions are in Appendix-Table A1. Standard errors are clustered at restaurant level and are reported in the parentheses. The regression is based on our linked restaurant loan-level panel sample where rating is calculated as the average for each month. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.)×I(FT)×GS_{city}	2.97***	2.73***	3.78***	2.14	1.00	5.45	-0.00	-0.07
	(0.65)	(0.71)	(1.39)	(1.55)	(1.58)	(5.46)	(0.10)	(0.13)
I(Afri.)×I(FT)×GS_{zip}	-17.60***	-16.22***	-22.80***	-13.20	-5.81	-32.34		
	(3.61)	(4.01)	(8.13)	(9.02)	(8.97)	(31.67)		
I(Asia.)×I(FT)×GS_{city}	0.75	1.43	2.24	3.04**	2.93	7.38	2.88	-0.23
	(1.04)	(0.99)	(1.41)	(1.30)	(4.46)	(6.60)	(2.92)	(3.35)
I(Asia.)×I(FT)×GS_{zip}	-4.66	-8.62	-13.22	-17.79**	-16.92	-42.65	-16.80	1.45
	(6.02)	(5.74)	(8.16)	(7.53)	(25.89)	(38.29)	(16.95)	(19.44)
I(Hisp.)×I(FT)×GS_{city}	1.08	1.28	1.17	0.71	0.97	16.78***	1.29	26.84***
	(1.05)	(1.14)	(1.28)	(1.27)	(8.23)	(1.78)	(0.97)	(2.18)
I(Hisp.)×I(FT)×GS_{zip}	-6.31	-7.39	-6.86	-4.14	-5.40	-97.13***	-8.13	-156.70***
	(6.12)	(6.64)	(7.42)	(7.36)	(47.77)	(10.28)	(5.57)	(12.62)
I(FT)	0.05***	0.06***	0.05***	0.04***	-0.07*	-0.07	-0.06	-0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.07)
I(African)	0.11***	0.14***	0.04	0.04	0.04	0.23	-0.17	-0.12
	(0.03)	(0.03)	(0.04)	(0.05)	(0.12)	(0.14)	(0.13)	(0.16)
I(Asian)	-0.09***	-0.07***	-0.03***	-0.03***	-0.14***	-0.13***	-0.03	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
I(Hispanic)	-0.09***	-0.09***	-0.11***	-0.11***	-0.12***	-0.08	-0.15***	-0.10*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.04)	(0.06)
Employment	-0.21***	-0.20***	-0.18***	-0.19***	-0.69***	-0.79***	-0.61***	-0.84***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.11)	(0.18)	(0.13)	(0.19)
I(Franchise)	-0.88***	-0.86***	-1.05***	-1.00***	-0.87***	-0.77***	-0.89***	-0.76***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)	(0.08)	(0.08)	(0.11)
Monthly FEs	Yes	No	Yes	No	Yes	No	Yes	No
City × Monthly FEs	No	Yes	No	Yes	No	Yes	No	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	923684	867831	416233	387260	47542	26314	24066	13059
Adjusted R^2	0.043	0.065	0.049	0.069	0.038	0.048	0.039	0.046

Table B9 Non-Federally Insured Lenders and Minority Borrowers

This table reports the linear probability regression results of specifications where the dependent variable is the *Uninsured* loan indicator (0/1) that equals to one if the lender is not a federally insured financial institution. We restrict to the sample matched with FFEIC as to have clear information on whether the lender is federally insured. In pane A and B, we report results on the 2020 PPP and 2021 PPP, respectively. *Minority*, *African*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. Matched sample construction and control variables are the same as in Table 2. Standard errors are clustered at city level. The regression is based on our linked restaurant-loan-level cross-sectional sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	*I*(Uninsured) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	0.16**	0.17**	0.12*	0.13*				
	(0.07)	(0.08)	(0.07)	(0.08)				
I(African)					1.00*	0.70	0.99*	0.70
					(0.58)	(0.56)	(0.59)	(0.57)
I(Asian)					0.27***	0.26**	0.22**	0.20*
					(0.10)	(0.11)	(0.10)	(0.11)
I(Hispanic)					-0.03	0.02	-0.05	0.01
					(0.08)	(0.08)	(0.08)	(0.08)
Employment	-0.00***	-0.00***	-0.01***	-0.00***	-0.00***	-0.00***	-0.01***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I(Franchise)	-0.42***	-0.28***	-0.43***	-0.29***	-0.41***	-0.27***	-0.43***	-0.29***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	85349	81702	79145	75502	85349	81702	79145	75502
Adjusted R^2	0.001	0.053	0.001	0.052	0.001	0.053	0.001	0.052

Panel B: 2021 PPP First Draw

Dep. Var.	*I*(Uninsured) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	1.14***	0.25	1.20***	0.29				
	(0.38)	(0.54)	(0.39)	(0.56)				
I(African)					-0.64***	-0.62	-0.62***	-0.66
					(0.22)	(0.54)	(0.23)	(0.56)
I(Asian)					2.21***	0.88	2.27***	0.90
					(0.57)	(0.70)	(0.58)	(0.72)
I(Hispanic)					-0.26	-0.64	-0.21	-0.57
					(0.32)	(0.46)	(0.32)	(0.47)
Employment	-0.00	-0.02**	-0.01	-0.04**	0.00	-0.01*	-0.00	-0.03**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
I(Franchise)	-0.55*	-1.79***	-0.46	-1.80**	-0.55*	-1.77***	-0.47	-1.79**
	(0.32)	(0.66)	(0.32)	(0.70)	(0.32)	(0.66)	(0.32)	(0.70)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	5298	3321	5079	3184	5298	3321	5079	3184
Adjusted R^2	0.004	0.037	0.004	0.038	0.008	0.038	0.009	0.039

Table B10 Restaurant Ratings (Non-Federally Insured Lenders)

This table reports the regression results examining the difference in restaurant ratings between minority and non-minority borrowers who are matched with non-federally insured and federally insured lenders. The dependent variable is the *Rating Stars*, within the range of 0 to 5, based on the customer reviews from yelp.com. We restrict to the sample matched with FFEIC as to have clear information on whether the lender is federally insured. In pane A and B, we report results on the 2020 PPP and 2021 PPP, respectively. *African*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The variable *Uninsured* is defined to be 1 if the lender is not a federally insured financial institution. Matched sample construction and control variables are the same as in Table 3. Standard errors are clustered at restaurant level. The regression is based on our linked restaurant loan-level panel sample where rating is calculated as the average for each month. The time period for the "Before Covid-19" sample is from April 2018 to March 2020, and the "During Covid-19" sample is from April 2020 to March 2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African) × *I*(Uninsured)	0.02	0.02	0.04	0.04	-0.16	-0.24	-0.14	-0.23
	(0.26)	(0.25)	(0.26)	(0.26)	(0.30)	(0.27)	(0.30)	(0.27)
I(Asian) × *I*(Uninsured)	-0.05	-0.09	-0.05	-0.10	-0.08	-0.08	-0.07	-0.08
	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)	(0.10)	(0.09)	(0.10)
I(Hispanic) × *I*(Uninsured)	-0.17	-0.16	-0.17	-0.16	-0.09	-0.02	-0.09	-0.03
	(0.11)	(0.11)	(0.11)	(0.12)	(0.16)	(0.17)	(0.16)	(0.17)
I(Uninsured)	-0.04	0.03	-0.04	0.03	-0.05	-0.04	-0.06	-0.04
	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	952321	895771	882486	826845	427705	398417	396912	368112
Adjusted R^2	0.047	0.068	0.043	0.065	0.052	0.073	0.048	0.069

Panel B: 2021 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African) × *I*(Uninsured)	-	-	-	-	-	-	-	-
I(Asian) × *I*(Uninsured)	-0.09	0.17	-0.08	0.13	-0.16	-0.18	-0.20	-0.18
	(0.22)	(0.41)	(0.21)	(0.41)	(0.20)	(0.37)	(0.20)	(0.38)
I(Hispanic) × *I*(Uninsured)	0.85***	0.75	0.82***	0.75	0.59***	0.12	0.52***	0.12
	(0.19)	(0.48)	(0.19)	(0.48)	(0.15)	(0.34)	(0.15)	(0.34)
I(Uninsured)	-0.13	-0.14	-0.12	-0.14	-0.05	0.20	0.00	0.20
	(0.18)	(0.41)	(0.18)	(0.40)	(0.14)	(0.32)	(0.13)	(0.32)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	43203	22546	41716	21715	21815	11194	20931	10694
Adjusted R^2	0.040	0.048	0.040	0.048	0.040	0.041	0.038	0.036

Table B11 Savings & Loan Association and Minority Borrowers

This table reports the linear probability regression results of specifications where the dependent variable is the *S&L* loan indicator (0/1) that equals to one if the lender is a Savings & Loan Association. We restrict to the sample matched with FFEIC as to have clear classification of S&L. In pane A and B, we report results on the 2020 PPP and 2021 PPP, respectively. *Minority*, *African*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. Matched sample construction and control variables are the same as in Table 2. Standard errors are clustered at city level. The regression is based on our linked restaurant-loan-level cross-sectional sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	I(S&L) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	-0.06**	-0.04	-0.05*	-0.04				
	(0.03)	(0.03)	(0.03)	(0.03)				
I(African)					-0.18***	-0.13*	-0.18***	-0.13*
					(0.03)	(0.08)	(0.03)	(0.07)
I(Asian)					-0.09***	-0.06**	-0.09***	-0.07**
					(0.03)	(0.03)	(0.03)	(0.03)
I(Hispanic)					-0.01	0.00	-0.00	-0.00
					(0.04)	(0.04)	(0.04)	(0.04)
Employment	0.00	0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I(Franchise)	-0.04	-0.05	-0.04	-0.05	-0.04	-0.05	-0.04	-0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	85349	81702	79145	75502	85349	81702	79145	75502
Adjusted R^2	-0.000	0.160	-0.000	0.157	-0.000	0.160	-0.000	0.157

Panel B: 2021 PPP First Draw

Dep. Var.	I(S&L) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	-0.40***	-0.26	-0.29***	-0.29*				
	(0.11)	(0.16)	(0.10)	(0.18)				
I(African)					-0.38***	-0.12	-0.33***	-0.12
					(0.12)	(0.08)	(0.11)	(0.08)
I(Asian)					-0.38***	-0.32*	-0.28***	-0.36*
					(0.11)	(0.19)	(0.10)	(0.21)
I(Hispanic)					-0.42***	-0.17	-0.28***	-0.19
					(0.12)	(0.13)	(0.10)	(0.13)
Employment	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I(Franchise)	-0.01	-0.07	-0.26***	-0.11*	-0.00	-0.07	-0.26***	-0.11*
	(0.33)	(0.05)	(0.09)	(0.07)	(0.33)	(0.05)	(0.09)	(0.07)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	5298	3321	5079	3184	5298	3321	5079	3184
Adjusted R^2	0.002	0.109	-0.001	0.184	0.001	0.109	-0.001	0.183

Table B12 Restaurant Ratings (Savings & Loan Association)

This table reports the regression results examining the difference in restaurant ratings between minority and non-minority borrowers who are matched with savings & loan associations and other lenders in the FFIEC list. The dependent variable is the *Rating Stars*, within the range of 0 to 5, based on the customer reviews from yelp.com. We report results on the 2020 PPP. Number of observations for minority racial groups matched with S&Ls is not enough in the 2021 PPP and thus no results are reported. *African*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *S&L* is defined to be 1 if the lender is a Savings & Loan Association. Matched sample construction and control variables are the same as in Table 3. Standard errors are clustered at restaurant level. The regression is based on our linked restaurant loan-level panel sample where rating is calculated as the average for each month. The time period for the "Before Covid-19" sample is from April 2018 to March 2020, and the "During Covid-19" sample is from April 2020 to March 2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African) × *I*(S&L)	-	-	-	-	-	-	-	-
I(Asian) × *I*(S&L)	0.06	0.14	0.09	0.14	0.26*	0.41**	0.28**	0.41**
	(0.19)	(0.18)	(0.19)	(0.18)	(0.14)	(0.17)	(0.14)	(0.18)
I(Hispanic) × *I*(S&L)	0.11	0.03	0.14	0.05	0.12	0.17	0.14	0.17
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
I(S&L)	0.02	0.05	-0.02	0.05	0.10	0.06	0.07	0.04
	(0.06)	(0.07)	(0.07)	(0.08)	(0.06)	(0.08)	(0.07)	(0.09)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	952321	895771	882486	826845	427705	398417	396912	368112
Adjusted R^2	0.047	0.068	0.043	0.065	0.052	0.073	0.048	0.069

Table B13 Capacity: Fintech vs Non-Fintech

This table reports the mean and standard deviation (in square brackets) of lender capacity, as measured by the number of loans disbursed in the PPP program in 2020 (upper panel) and in 2021 (lower panel) by fintech and non-fintech lenders, and the t-test results of the differences in capacity between fintech and non-fintech lenders. t-value are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2020 PPP First Draw			
	Fintech	Non-Fintech	Diff.
N. Loans	31052.79	617.85	-30434.9***
	[36602.76]	[6865.01]	(-27.75)
Observations	53	4199	
2021 PPP First Draw			
	Fintech	Non-Fintech	Diff.
N. Loans	12238.85	294.05	-11944.8***
	[34414.21]	[2803.07]	(-17.68)
Observations	46	4062	

Table B14 Approval Date (Robustness – Restricted Starting Date for the 2020 PPP)

This table reports the robustness check results of the 2020 PPP program in Table 5 by limiting the sample period to starting from April 9, 2020 because fintech lenders are not formally allowed in the program in the first week (April 03, 2020- April 08, 2020). In particular, as indicated in column heads, we do two groups of robustness checks by limiting the 2020 PPP sample to: 1) starting from April 09, 2020; 2) focusing on the second tranche in the 2020 PPP that started from April 27, 2020. The regression examine the difference in PPP loan approval date between minority and non-minority borrowers who are matched with fintech and non-fintech lenders. The dependent variable is the *Δ(Approval Date-PPP Starting Date)*, where the starting date is April 03,2020 and Jan 12, 2021 for the 2020 and 2021 program correspondingly. *African*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. Matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, business type (aggregated), food price range, and with a difference of at most five employees in employment size. In addition to the variables reported in the table, we also control for city and business type fixed effects. Detailed variable definitions are in Appendix-Table A1. Standard errors are clustered at city level. The regression is based on our linked restaurant loan-level cross-sectional sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Δ(Approval Date-PPP Starting Date)							
	From April 9, 2020				From April 27, 2020			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African) × *I*(Fintech)	-2.00	-1.49	-2.00	-1.40	0.42	-0.68	0.39	-0.52
	(3.15)	(3.29)	(3.14)	(3.29)	(3.16)	(3.42)	(3.16)	(3.42)
I(Asian) × *I*(Fintech)	3.45***	3.68***	3.63***	3.88***	5.35***	4.22***	5.44***	4.38***
	(0.73)	(0.76)	(0.74)	(0.77)	(0.75)	(0.78)	(0.75)	(0.79)
I(Hispanic) × *I*(Fintech)	1.41	0.55	1.43	0.61	3.72***	2.87**	3.72***	2.94**
	(1.12)	(1.16)	(1.12)	(1.16)	(1.18)	(1.25)	(1.17)	(1.25)
I(Fintech)	12.10***	10.72***	11.61***	10.20***	7.75***	7.81***	7.46***	7.45***
	(0.46)	(0.50)	(0.47)	(0.51)	(0.47)	(0.51)	(0.47)	(0.51)
I(African)	7.63***	6.30***	7.12***	5.75***	3.61***	3.03**	3.44***	2.90**
	(1.26)	(1.31)	(1.27)	(1.33)	(1.31)	(1.36)	(1.33)	(1.38)
I(Asian)	8.60***	7.88***	8.12***	7.42***	4.24***	4.39***	4.13***	4.26***
	(0.30)	(0.32)	(0.30)	(0.32)	(0.29)	(0.31)	(0.29)	(0.31)
I(Hispanic)	4.56***	4.33***	4.44***	4.22***	1.69***	1.94***	1.74***	1.94***
	(0.28)	(0.30)	(0.29)	(0.30)	(0.33)	(0.35)	(0.33)	(0.35)
Employment	-0.08***	-0.08***	-0.18***	-0.18***	-0.07***	-0.06***	-0.14***	-0.12***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
I(Franchise)	-7.22***	-7.24***	-7.02***	-7.15***	-5.62***	-5.35***	-5.49***	-5.17***
	(0.23)	(0.25)	(0.25)	(0.27)	(0.31)	(0.35)	(0.32)	(0.37)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	81687	78026	76850	73244	56715	53348	54437	51109
Adjusted R^2	0.114	0.135	0.117	0.137	0.066	0.085	0.068	0.087

Appendix C Data Construction

Appendix C1 Identify Fintech Lenders

The principle source of the fintech company list we used for our study is from the SBA official website as well as the local SBA websites. We start with the fintech company list published on sba.gov.[1] We manually read the PPP lender list published on the local SBA website of all states and find that the state of Arizona, California, Maryland, and North Carolina include a section on non-traditional lenders in their PPP lender lists. We include those lenders in the fintech company list as well. Finally, we also expand the list by consolidating lists from news sources below.

1. https://www.inc.com/brit-morse/fintechs-small-business-ppp-loan-applications.html
2. https://www.lendacademy.com/all-of-the-fintechs-involved-in-ppp-loans/
3. https://www.uschamber.com/co/run/finance/list-of-fintech-companies-offering-ppp-loans

We manually go through the entire sample of 165 non-bank lenders in the PPP loan-level dataset and do not identify any lenders that are clearly a fintech company but not appeared in the above described sources. Some non-bank lenders may have collaborations with fintech companies but we do not include those cases because banks may also cooperate with fintech companies in some degree[2]. It is very time consuming and might be impossible to identify all the partnerships between fintech companies and banks and other lenders, without adding more insights to our analysis.

Since the lists published on SBA websites and other news sources are primarily aimed to help borrowers to find a suitable platform or place to apply for the PPP loan, they may show the name of the lending platform instead of the lender backing the loan, and therefore not the same as the lender recorded in the PPP dataset. For each fintech company, we manually read their website and google search related information so as to identify the potential lender(s) associated with it. Table C1-1 presents the consolidated fintech company list and the lender shown in the PPP dataset.

[1]https://www.sba.gov/sites/default/files/resource_files/Fintech_Companies_Participating_in_PPP_05.08.20_0.pdf

[2] An example of unclear fintech lending of non-bank lenders in PPP: FundEx Solutions Group… representing the best of both traditional lending and fintech. An example of partnerships between fintech companies with other PPP lenders is "CNote has entered into a partnership with The Entrepreneur Fund to serve as a new capital source." Examples of banks work with fintech companies: Ally Bank, Bank of Hope, and Citizens Business Bank, etc. are shown to work with Lendistry in PPP.

In the table, we also indicate whether the fintech company is listed in the SBA or local SBA PPP lender list.

Table C1-1 Fintech company list and match with lender name in PPP data

Fintech company	SBA	AZ	MA	NC	CA	Lender Name in PPP
Biz2credit	Y			Y		Itria Ventures LLC; Loan Source Incorporated
BlueVine	Y	Y	Y	Y	Y	Cross River Bank
Brex + Womply*	Y					-
Credibly	Y	Y				-
Cross River Bank	Y			Y		Cross River Bank
Divvy	Y			Y		Cross River Bank
Forwardline Financial LLC		Y				FinWise Bank
Fundbox	Y	Y			Y	Fundbox, Inc.
Fundera*	Y			Y		-
Funding Circle	Y	Y	Y	Y	Y	FC Marketplace, LLC (dba Funding Circle)
Intuit (Quickbooks)	Y	Y	Y	Y	Y	Intuit Financing Inc.
Kabbage	Y	Y	Y	Y	Y	Kabbage, Inc.; Celtic Bank Corporation
Lendio	Y		Y	Y		Sunrise Banks, National Association
Lendistry			Y			BSD Capital, LLC dba Lendistry
NAV*	Y					-
OnDeck	Y	Y	Y		Y	Celtic Bank Corporation
Opportunity Fund Community Development		Y			Y	Opportunity Fund Community Development
Paypal	Y	Y	Y		Y	WebBank
Ready Capital	Y					Readycap Lending, LLC
Reliant Funding						Cross River Bank
SmartBiz*						-
Square	Y	Y	Y		Y	Celtic Bank Corporation
Veem	Y					Cross River Bank

* Partner with multiple lenders and do not find the fintech company itself in the PPP data

Appendix C2 Lenders Classifications and Matching with FFIEC

This appendix describes our lender classifications and how we match the PPP lenders with Federal Financial Institutions Examination Council (FFIEC) financial institutions. Based on the matched list of PPP and FFIEC lenders, we show how we define several key variables.

1. Lender Classification

To save some labor effort in the matching process with FFIEC, we first classify the PPP lender list into banks and non-banks. Within the non-banks, we classify lenders into CDFI/CDC, fintech non-banks, other non-banks.

1.1 Non-Banks

We start with the full list of 5,597 PPP lenders in the entire PPP and PPS dataset. The first step is to classify the lenders into banks (including savings, credit unions, farm credit system institutions, etc.). We use regular expressions on lender names, and define the lender as a bank if either the name of the originating and the servicing lender[3] satisfies the regular expression. Examples of regular expressions are containing "bank", ends with "N.A." or "National Association", and containing "Production Credit Association". For the part that does not containing expressions satisfying the regular expressions, and therefore in the list of non-banks, we manually checked them by searching on the official website and names and reassign 47 lenders into the bank list, such as AB&T, BBVA USA and Choice Financial Group. This gives us 5,472 banks and 125 non-banks.

1.2 CDFI Loan Funds and 504 CDC

For the purpose of our study, we further classify the non-banks into lenders that have a higher weights on community development and other non-bank lenders. We use two sources of information. First, we match the PPP lenders with the loan funds in the official list of "List of Certified Community Development Financial Institution (CDFIs) with Contact Information as of October 14, 2020" published on cdfifund.gov using exact name match. This gives 42 matches considering either the servicing and originating lender is among the CDFI list. This step also

[3] The difference between the servicing and originating lender is most relevant for fintech lenders and CDFIs, which we address in particular. For other lenders, the servicing and originating lender is the same.

adjusts one lender in the bank list, Hope Enterprise Corporation, into the non-bank list. In particular, one fintech lender in our list, Opportunity Fund Community Development, is also a CDFI. For the rest 85 non-bank lenders, we manually check them with the official CDFI list and find 24 pairs of matched lenders. In the manual step, we also consider match with either the servicing or the originating lender as valid matches.

Second, we identify Certified Development Company (CDC) using the list of lenders that participated in previous 504 programs. We adjust lender names use the lender cleaning code as in the process of other steps related to previous lenders. All identified CDCs are non-banks under our classification. We do not consider other non-banks whose name containing words like "community", and "development" but neither in the CDFI or the CDC list as community development related lenders as company name is not a precise indication.

In total, we identify 66 CDFIs and 23 CDCs, with 8 enter in both category.

1.3 Fintech Non-Banks

Using our list of fintech lenders, we identify 14 fintech lenders in the non-bank part.

1.4 Other Non-Banks

After restricted to non-fintech lenders, we classify the rest 35 non-bank lenders in the category of other non-banks. As stated in the appendix describing our process to identify fintech lenders, we manually google searched more information for each lender and do not find any lender is clearly stated as a fintech lender.

Code of the regular expressions, manually adjusted lender lists, and the final list of non-banks can be found on the corresponding author's website. Table C2-1 summarizes the number of pairs of originating and servicing lenders in each category.

Table C2-1 Number of Lender Pairs in Each Category

Category		N. in the entire PPP sample	N. in our final analysis sample
Banks	Fintech	49	42
	Non-fintech	5,420	4,134
Non-Banks	CDFI/CDC	81 (2 are also fintech lenders)	54 (2 are also fintech lenders)
	Fintech	14	11
	Others	35	27

2. Matching PPP Lenders with FFIEC

We then match the PPP lenders with financial institutions on the FFIEC list. Our starting sample is 3,695 PPP lenders who 1) are lenders in our final linked restaurant sample; 2) lend more than 100 loans in the entire PPP program; 3) banks (including fintech lenders) or other non-banks (excluding CDFI/CDC/fintech lenders) classified in step 1 described above.

Federal Financial Institutions Examination Council (FFIEC) lender information provides information on financial institutions for which the Federal Reserve has a supervisory, regulatory, or research interest, which includes a full list of depository institutions, as well as some non-depository financial companies. The data includes both active and the last instance of closed financial institutions and assigns a unique identifier (*ID RSSD*) for each financial institution. We keep financial institutions that are active in and after 2020 because PPP loans are originated after 2020. The data is available from the FFIEC website (ffiec.gov).

In the code-based matching step, we find a match among the FFIEC financial institutions for each PPP lender that have the same name in the same city. We use originator name, city, and state information from PPP. We use bank legal name from FFIEC. The city and state information that we use from FFIEC is the lender's headquarter physical location city. We search for different variants of the lender name in our matching process. For example, "XX FCU" in place of "XX Federal Credit Union". Given that we are searching within city, the matched is very unlikely to be a mismatch. This gives a total match of 3,511 lenders.

For the remaining 184 unmatched lenders, we manually search for the lender name from FFIEC website and match with the FFIEC lender with the same name (including same name but different variants), different city, but the FFIEC lender city is within 30miles distance from the PPP lender city in the same state. This gives a total match of 3,658 lenders. The remaining 37 unmatched lenders are classified as financial companies that are not included in the FFIEC lender sample.

The FFIEC website also provides Branch Data which are the last instance of branches whose head office is listed in the financial institution file. We include branches that are active in and after 2020. For PPP lenders with a matched *ID RSSD* identifier, we match the PPP lender with branch's parent institutions, therefore, we can identify the branches that belongs to each lender. For those PPP lenders with either no branch information from FFIEC branch data, or no *ID RSSD* identifier, we classify them stand alone entities.

3. Further Classification for FFIEC Matched Lenders

For lenders matched with FEIEC, we classify lenders into banks vs non-banks, federally insured institutions vs non-federally insured institutions, credit union vs non-credit union, savings & loan association vs non- savings & loan association based on lender information from FFIEC.

Bank: We use a broad definition of banks as any depository institutions. We identify depository institutions based on entity type from FFIEC lender information, including "Cooperative Bank", "Domestic Branch of a Domestic Bank", "Federal Credit Union", "Federal Savings Bank", "National Bank", "Non-member Bank", "Savings & Loan Association", "State Credit Union", "State Member Bank", and "State Savings Bank".

Federally Insured: A lender is classified as federally insured institution if its primary insurer is either National Credit Union Share Insurance Fund or Deposit Insurance Fund.

Credit Union: Lenders whose entity types are "Federal Credit Union" or "State Credit Union" are classified as credit unions.

Savings & Loan Association: Lenders with entity types as "Savings & Loan Association" are defined as Savings & Loan Association.

4. Cross Validation and Final Lender Classification

Based on the consolidated lender dataset, only two lenders (New York Business Development Corporation, and American Lending Center) identified as non-banks by name in section 1 are matched with the FFIEC list and their entity type is "Domestic Entity Other (DEO)". Among the banks identified by name and matched with the FFIEC list, only eight lenders are DEO; others are all in the bank group based on our classifications in step 3. Among the eight DEO lenders, five are farm credit institutions, and we adjust the rest three (First Western SBLC, Inc, Capital One, National Association, and First National Bank Texas) into the non-bank category. This gives additional validation of our code-based classification of banks and non-banks. Among the banks identified by name, only 17 are unmatched.

Appendix C3 Linking a Business Entity Participated in the Paycheck Protection Program with a Restaurant on Yelp.com

This appendix describes the steps that we follow to match businesses in the *Food Services and Drinking Places* sector (NAICS code that equals to 722) in the Paycheck Protection Program (PPP) to the restaurants on yelp.com. It also presents the matching criteria based on which we define a link between a business in the PPP and a restaurant on yelp.com. In addition, we provides the details on the name and address cleaning process which we use as the input of automatic search and code-based match.

1. Matching Steps

Our start sample is the 372,541 loans assigned to business in the *Food Services and Drinking Places* sector in the two tranches of the first draw of the PPP program in both 2020 and 2021, which are labeled with "PPP" by the *Processing Method* variable in the original dataset from SBA. In addition, our sample also covers 198,889 loans in the *Food Services and Drinking Places* sector in the second draw of the PPP program in 2021, which are labeled with "PPS" by the *Processing Method* variable. After our name and address adjustments, we are also able to identify the first draw participants who reapplied for the second draw.

Step 1: Basic sample cleaning

The basic sample cleaning serves for two purposes. First, by unifying and deleting suffix and prefix, the business name and address are more likely to be what appear on yelp.com, which facilitate our automatic search and code-based match process. Second, as we also study what types of borrowers participate in both the first and second draws of the PPP program, unifying and checking potential duplications makes the match across different years more reliable.

Step 1.1 Code-based adjustments of the business name

This step aims to adjust the names to be more likely to be what restaurants use as a trading name than a formal format of a company name. Details on the cleaning steps are described in *Section 3 Name and Address Cleaning Mapping*.

Step 1.2 Code-based adjustments of the business address

This step aims to adjust the addresses to be more likely to have a more unified format of different representations of the address code. Details on the cleaning steps are described in *Section 3 Name and Address Cleaning Mapping*.

Step 1.3 Manual check and adjustments potential duplicated business entities

The aim of this step is to assign a unique ID for each business entity participated in the PPP and PPS. We assume that business entities in the same zip code region with the same name are the same restaurant and assign the same business entity ID to them. More specifically, two observations in the original data will be assigned with the same business entity ID if 1) the business name in the original dataset and the 5-digit zip code are the same for the two parts of the dataset; or 2) the adjusted name, adjusted address and the 5-digit zip code are the same for the two parts of the dataset (the adjustment rules are described in *Section 3 Name and Address Cleaning Mapping*).

After excluding the repetition because of participation in both PPP and PPS, we have 3,500 observations that have the same adjusted business name and 5-digit zip code. We do two rounds of manual checks on this 3,500 observations. In the first round, we detect simple cases where the addresses are either exactly the same but written in different format (e.g., "1502 j f kennedy dr" and "1502 jfk drive") or with very small difference in the road number (e.g., "1651 w ogden ave" and "1659 w ogden ave"). We assign the same business entity ID to the two observations. After this round of check, we have a rest of 1,370 observations. Then, we do a second round of manual check and google search to gain additional information to decide whether the business name and address in the dataset are for the same restaurant. We also gain the yelp link alongside. We find the yelp links for 1,058 observations, with 529 pairs for the same restaurant where we assign the same business entity ID and 44 observations that are different restaurants.

After the above described steps, we assign 371,845 unique business entity IDs to the 372,541 loans (less than 1% of the businesses are potentially applying for multiple loans.) Around 60% of participants in PPP also participated in the PPS.

Step 1.4 Basic adjustments of the franchise names

This step adjusts the franchise names in the PPP data to be close to the franchise names in real life. As the total number of franchise names (1,496) is relatively small, we do this step manually. We detect and delete some franchise names that are not for restaurant chains and the sample size decreases to 372,298 loans for the PPP sample and 198,642 loans for the PPS sample.

Step 2: Code-based automatic search of the adjusted business name and address on yelp.com.

We employ both the name search and address search on yelp.com to take into account the possibility that either one is better than the other when search on yelp.com to find the most closely related restaurants. In both searches, we also include the zip code in the PPP data of the business entity to narrow the search range and increase the likelihood of a correct match. We use zip code instead of city because zip code is for a much smaller region than cities in the most cases. In addition, as the city information in the original PPP data is with a lot of typos, using zip code instead of city can immune us from the noise in the original data.

We start with the name search as it can provide a better match when the restaurant's name is related to its company name. Name search also gives results on restaurants that are closed. After the name search, we match the search outcomes with the original PPP sample based on the matching criteria described in *Section 2 Matching Criteria*. If no match is found, we move on to the address search. While the name search may also give the correct results when the restaurant uses a different name than its company name, we complement the search results with address search to have a higher matching rate. For time saving reasons, we include the first ten search results suggested by Yelp (i.e., the search outcomes on the first page on yelp.com) for our matching step. In most cases, Yelp search engine works with good precision and therefore it is very likely that the correct match is beyond the first ten results. Code for the search is available upon request.

One potential caveat in the search procedure is that the results suggested by Yelp might be incomplete and therefore we miss the correct match. However, as Yelp is a widely-used restaurant search engine with good reputation, such a possibility is low and unlikely to be systematically biased.

Step 3: Match based on the combination of name and address

Our matching criteria is rather strict as we only include the pair as "matched" when we are confident that both the name and address in the two data sources have meaningful connections. We also put the restriction that the restaurant found on yelp.com is in the same 5-digit zip code region as in the PPP data.

Step 3.1 Code-based adjustments of the names and addresses

We employ the same code-based adjustments of the names and addresses as described in *Section 3 Name and Address Cleaning Mapping* for the counter parts in yelp to have a uniform representation of the same name/address. This step is important for improving the matching precision. For franchise names, we further shorten the names from the version used for automatic search as the names on yelp.com is shorter in most cases[4]. Code for this shortening step is available on the corresponding author's website. We only do the shortening step for franchise names because for non-franchised restaurants, two might only differ in the suffix.

Step 3.2 Code-based matching of the names and addresses based on different criteria

We use code-based rule to narrow down and split the search outcomes into subsamples according to the connections between the PPP information and information on yelp.com for the adjusted and shortened version of the names and addresses. *Section 2 Matching Criteria* describes the detailed matching criteria.

Step 3.3 Manual check on a random sample for code-suggested matches under each criterion

To ensure the correctness of the matching process, we first manually check a random sample for the code-suggested matching sample for each criterion. For stricter matching criteria, the rate of correct matches is 100% or 98% and we consider all code-based matches under these criteria as "matched".

Step 3.4 Manual correction of the matches for subsamples where the code-suggested matches are of low precision.

[4] Having parts that indicate food type such as "bbq", "frozen", and "cupcakery" in the version of names used for search is good for the search per se because yelp tend to suggest searching outcomes of the same food type.

When a random check suggests precision lower than 95%, we manually check and correct all the code suggested matches.

After the steps above, we have a sample of 104,429 total matches. We also add in the 556 matches from the manual step in 1.1, so we have a sample of 104,985 matches until this step.

Step 3.5 Other adjustments

There are a very few cases where one loan is matched with several yelp links. We manually check them the 689 matches where the yelp link is duplicated. We pick the link that are more like to be a restaurant. For example, for some duplicates, one link is for a hotel and one link is for a restaurant in the hotel, then we pick the latter. When both links are for the same restaurant, we choose the one with more reviews or a more complete sample period before and after the Covid-19 crisis.

Until this step, we gain a matched sample for 104,296 loans, which accounts for 28.01% of the whole PPP sample in the *Food Services and Drinking Places* sector. Considering our rather strict matching criteria to ensure the likelihood of false positive to be very low, the matching rate is reasonable and the matched sample is useful. We further exclude the 1,769 observations where one yelp link is matched to multiple loans (1.70%, close to the percentage of potential multi-loan applications in the whole sample) and 724 observations where the yelp link is for a non-restaurant type business. We manually classify the business labels on yelp.com into labels for restaurants and for non-restaurants. We publish the list of 546 yelp business labels related to our sample and our classification on the corresponding author's website.

Our final sample consists of 101,803 matches between a PPP loan and a yelp link for restaurants. We further exclude borrowers in Puerto Rico, Northern Mariana Islands, Guam, U.S. Virgin Islands when doing analysis.

2. Matching Criteria

This section describes the criteria based on which we identify as a match between a business entity in the PPP data and a restaurant on yelp.com, ranked from the most strict to the least strict ones. All criteria consider both the name and the address of the business.

Criterion 1: name the same/containing, address the same/containing, at least one is the same (75.65%)

Criterion 1 identifies matches where both the names and addresses in the PPP data and the yelp search outcomes are either exactly the same or with a relationship of one containing the other. We pose a restriction that at least one (name or address) is exactly the same. We check a 100 random sample for each case of the different combination of name/address and exact/containing. In all cases, we have a 100% accuracy of matches for the random sample. Therefore, we consider all matches under criterion 1 are correct matches. Combining the matched search outcomes from both the name search and address search, we have 66,018 matches for non-franchise restaurants and 12,979 for franchise restaurants.

For the following criteria, we only consider the non-franchise sample because the following criteria are based on non-exact matching either for the name or the address which can only reasonably expand the matching sample for non-franchised restaurants. For names, since franchise names are already cleaned to a short version when used in the matching process and if there is no match found based on criteria 1, it is very unlikely to gain correct matches for a more relaxed criteria. In addition, franchise restaurant names are already trading names so they are what appeared on yelp.com. For non-franchised restaurants, relaxing restrictions on names might be useful since some restaurants' company name is quite different from the trading name. For addresses, non-franchised restaurants may put the corporation location or the business owner's home address in the PPP data and by relaxing matching to related restaurants in the same zip code region can mitigate this data issue. Franchised restaurants cannot put the corporation location, which is the headquarter of the brand, in the PPP loan application. Franchised restaurant owners may also put their home address in the PPP application but we consider this type of mis-input to be of a much lower percentage for franchised restaurant than for non-franchised restaurant as the separation between the business and the owner is clearer in franchised restaurant than in a family-owned restaurant. Besides, given the high possibility of multiple restaurants under the same franchise brand in the same zip code region, we cannot easily identify correct matches if the address in the PPP data is not correct.

Criterion 2: name the same, zip code the same (9.92%)

Criteria 2 identifies matches where both the name and the 5-digit zip code in the PPP data and the yelp search outcomes are exactly the same. We check a 100 random sample and have a 98% accuracy of matches. Therefore, we consider all matches under criteria 2 are correct matches. Combining the matched search outcomes from both the name and address searches, we have 10,361 matches for non-franchise restaurants.

Criterion 3: name containing, address containing, zip code the same (6.01%)

Criterion 3 identifies matches where both the names and addresses in the PPP data and the yelp search outcomes are with a relationship of one containing the other. In addition, we pose the restriction that PPP data and the yelp search outcome are in the same 5-digit zip code. We check a 100 random sample and have a 100% accuracy of matches. Therefore, we consider all matches under criteria 3 are correct matches. Combining the matched search outcomes from both the name and address searches, we have 6,279 matches for non-franchise restaurants.

Criterion 4: name containing, zip code the same, with manual check and correction for all observations (8.42%)

Criterion 4 identifies where the names in the PPP data and the yelp search outcomes are with a relationship of one containing the other. In addition, we pose the restriction that PPP data and the yelp search outcome are in the same 5-digit zip code. We do not pose the condition that the addresses in both data sources have a containing relationship. We check a 100 random sample and the accuracy is low. Therefore, we manually check all code suggested results and adjust the match when the one suggested by code matching is incorrect. After the manual correction, we have 8,792 matches for non-franchise restaurants, combining the matched search outcomes from both the name and address searches. Among them, 86.98% of the code matches are correct, with 6,225 are of address like typos or different format, 1,283 are of addresses either or a home address or corporation office, 513 of a wrong yelp address. We correct the rest of the sample with a better match by google for additional information.

3. Name and Address Cleaning Mapping

3.1 Franchise Names

The 2021 March release of the data offers the franchise name of each small business if the company is a franchise chain company. For example, for subway, in the PPP loan-level data, the variable *FranchiseName* is "Subway", and the variable *BorrowerName,* standing for the company name, can be "2 FRIENDSIN 2ND AVE INC.", "AKOTA CORP.", "FRESH SUBWAY 62 LLC", etc. Since yelp.com shows the franchise brand name of the restaurants, we use the *FranchiseName* as the search input, instead of using the *BorrowerName* as in the search for non-franchised restaurants.

Early data entries of the PPP data might be incomplete and therefore we adjust the franchise name across the PPP and PPS whenever the franchise name is available for the same business entity ID.

We manually check the franchise names for the part of borrowers whose digit NAICS code starts with 722 (*Food Services and Drinking Places*). This step improves data quality in two dimensions. First, by unifying the franchise name into the brand name on yelp.com, the search and match procedure will be more accurate and thus can give us more correct PPP-Yelp matches. For example, the original franchise name can be "starbucks master licensing agreement" which contains parts ("master licensing agreement") that are not related to the restaurant chain brand. Second, we detect franchise names that are clearly non-food services and drinking places. For instance, "Lamborghini America - dealer agreement" is a car brand, and "Laptopxchange" is an electronic service chain. We describe below the details on the criteria we use to judge whether the franchise name is a food or drinking place.

1) If the franchise name ends with the following key words, we consider it as a food or drinking place: bagel, baguette, bakery, bar and grill/grill/grill and bar/grill and wings/ grill & cantina/ bar-b-que, bistro, bowl(s), burger(s), burrito, cafe/café, cakes, cantina, cha, chicken(s) (& biscuits), chocolate & gelato, coffee (shop), cookie dough/cookie(s), cuisine, custard, deli, dessert, donuts, eatery, frozen yogurt, gelato & caffe, hot dogs, iced creamery/ ice cream, juice (bar), kitchen, noodles/noodle, pretzel (or starting with), restaurant (including mis-spelling: resturant), salad, sandwich (shop), smoothies,

steakhouse/ steak house, street food, subs, sushi, tacos (or starting with taco)/taco shop, taphouse, taverna, tea(s), pasta, pizza/ pizzeria, wings, yogurt

2) If not, we search the franchise name in google with restriction of only yelp.com webpages. If the search result returns a webpage in the restaurant/food category, we consider it as a food or drinking place. If all the search results on the first outcome page are not in the restaurant/food category, we google and check whether it is another type of franchise chains or not.

   Common mis-categorized franchise names are of art studio, car dealers, elderly care services, fitness clubs, optometrists, and training programs.

3) We do not exclude hotels in this step because some hotels also held an eating place. We exclude yelp pages of hotels in the manual matching step and the final other adjustment step.

Among the 1,496 (1,332 for PPP only) franchise names associated with entries of a NACIS code that starts with 722, 201 (145) names are not associated with restaurants, accounting for 490 (243) loans. 52,080 (32,283) loans whose borrowers are of a NACIS code that starts with 722 are with a franchise name representing a restaurant chain. The false positive error rate is less than 1\% on the loan level. We drop the observations where the franchise name is not so we have 372,298 loans for the PPP sample and 198,642 loans for the PPS sample.

The full list of the adjusted and the original franchise names in the original PPP data of a NACIS code that starts with 722 is available on the corresponding author's website. In the list, we generate a name for the search step. We put "1" if the original name is clearly not for food services or drinking places, and the shortened brand name otherwise.

3.2 Non-franchised names

Non-franchised restaurants account for the majority of the sample, 340,015 loans (or 91.27%) after the adjustment of franchise names across the PPP and PPS sample. The large sample size makes it impossible to do manual adjustments and therefore we do code-based adjustments by deleting suffix such as "corporation", "llc", "ltd". This serves the purpose to make the business name from the PPP data look more close to the potential restaurant trading name and facilitates the automatic search step. The cleaning code is on the corresponding author's website.

3.3 Address

The address cleaning step aims to cope with mainly two issues. First, it can unify the expressions across different data entries, for example, some entries may use “avenue” while some entries use “ave” for the same road type. Second, it also links more closely to the way addresses are expressed on yelp.com. The cleaning code is on the corresponding author’s website.

3.4 Examples Before and After Cleaning

Table C3-1 presents a sample of 10 random entries of the business name and address before and after adjustments.

Table C3-1

loannumber	businessname	businessname_org	address	address_org
4374000000	july 96	july 96 corp	2441 broadway	2441 broadway
4219000000	pb rams investment group	pb rams investment group	102 s main st	102 s main st
3521000000	ahta zahkung	ahta zahkung	318 hunt dr	318 hunt drive.
5662000000	k&a subs tyrone	k&a subs tyrone llc	3832 tyrone blvd	3832 tyrone blvd
8901000000	2 amegos	2 amegos inc	119 union st	119 union st
9764000000	la eda's restaurant	la eda's restaurant	1723 grand blvd	1723 grand blvd
1845000000	temple bill grill gp	temple bill grill gp	9768 bottoms rd	9768 bottoms road
7163000000	frankies other place	frankies other place inc	16036 red arrow hwy	16036 red arrow hwy
5586000000	summermoon coffee cedar valley	summermoon coffee cedar valley llc	1803 yaupon valley rd	1803 yaupon valley rd
1134000000	molly's corral	molly's corral llc	1519 w river rd	1519 west river road

4. Examples of the Linked Sample

Table C3-2 presents a sample of 10 random entries from our final linked sample on the PPP data and restaurant on yelp.com.

Table C3-2

https://www.yelp.com/biz/rockin-taco-and-tex-mex-frisco			
loannumber	franchisename	businessname_org	address_org
2244000000		rockin taco & tex mex llc	6890 main st ste c
https://www.yelp.com/biz/dunkin-schenectady-3			
loannumber	franchisename	businessname_org	address_org
2703000000	dunkin' donuts	schenectady donuts inc	1200 state st
https://www.yelp.com/biz/grimaldis-luna-park-east-syracuse-2			
loannumber	franchisename	businessname_org	address_org
3715000000		grimaldi's luna park inc	6430 yorktown circle
https://www.yelp.com/biz/biergarten-los-angeles-4			
loannumber	franchisename	businessname_org	address_org
4760000000		biergarten	206 n. western avenue
https://www.yelp.com/biz/pizza-market-west-newton			
loannumber	franchisename	businessname_org	address_org
5312000000		hanna gakob inc (pizza market)	69 river street
https://www.yelp.com/biz/vitales-clam-bar-berlin			
loannumber	franchisename	businessname_org	address_org
7926000000		vitale's clam bar llc	41 clementon rd
https://www.yelp.com/biz/hidden-fortress-coffee-roasting-watsonville			
loannumber	franchisename	businessname_org	address_org
8055000000		hidden fortress coffee roasting llc	125 hangar way #270
https://www.yelp.com/biz/gaucho-parrilla-argentina-pittsburgh			
loannumber	franchisename	businessname_org	address_org
8144000000		gaucho parrilla argentina	1601 penn ave
https://www.yelp.com/biz/club-37-baldwin			
loannumber	franchisename	businessname_org	address_org
8196000000		club 37 inc	3803 n m 37
https://www.yelp.com/biz/five-spice-omaha-2			
loannumber	franchisename	businessname_org	address_org
8863000000		five spice inc	2571 south 177th plaza

5. Sample Comparison: Linked versus Unlinked

Table C3-3 compares the summary statistics of key variables between PPP restaurant borrowers with a Yelp link and PPP restaurant borrowers without a Yelp link. The linked and unlinked sample looks similar to a reasonable degree.

Table C3-3

This table reports the mean of key variables between PPP restaurant borrowers with and without a Yelp link. The sample includes all restaurants borrowers in the PPP program in both years.

Panel A: PPP restaurant borrowers			
	UnLinked	Linked	Total
Initial Approval Amount	103368	77236	96221
Current Approval Amount	102801	77030	95753
Approved Date	06/27/2020	05/19/2020	06/16/2020
Jobs Reported	21	18	20
Franchise	0.074	0.121	0.087
Business Type:			
Corporation	0.292	0.339	0.304
Limited Liability Company	0.358	0.388	0.366
Partnership	0.024	0.030	0.025
Subchapter S Corporation	0.116	0.140	0.123
Sole Proprietorship	0.159	0.094	0.141
Self Employed	0.030	0.006	0.024
Others	0.021	0.003	0.016
Observations	270,432	101,799	372,231
Panel B: PPP restaurant borrowers(Excluded Sole Proprietorship, Self Employed and Others)			
	UnLinked	Linked	Total
Initial Approval Amount	125372	82719	112592
Current Approval Amount	124691	82398	112020
Approved Date	5/21/2020	5/18/2020	5/20/2020
Jobs Reported	25	19	23
Franchise	0.092	0.132	0.104
Business Type:			
Corporation	0.369	0.377	0.372
Limited Liability Company	0.454	0.432	0.448
Partnership	0.030	0.034	0.031
Subchapter S Corporation	0.147	0.157	0.150
Observations	213,484	91,326	304,810

Table C4-4 shows the fintech share between PPP restaurants borrowers with a Yelp link and those without a Yelp link in each business type. For business type of Corporation, Limited Liability Company, Partnership, Subchapter S Corporation, and Self Employed, the fintech share is similar for linked and unlinked samples. Restaurants with business type as Sole Proprietorship and Others have much a higher degree of fintech usage. Those are relatively smaller "restaurants" with limited type of services, for example, food trucks. Moreover, restaurants of a business type as Sole Proprietorship and Others are less likely to have a valid Yelp link, compared with other types of restaurants (see Table C4-4).

Table C3-4

This table reports the fintech share between PPP restaurant borrowers with and without a Yelp link for each business type. The sample includes all restaurant borrowers in the PPP.

Business Type	UnLinked FinTech	Obs.	Linked FinTech	Obs.	Total FinTech	Obs.	Link Rate
Corporation	0.096	78865	0.101	34474	0.097	113339	0.304
Limited Liability Company	0.085	96931	0.085	39490	0.085	136421	0.289
Partnership	0.076	6374	0.089	3065	0.081	9439	0.325
S Corporation	0.087	31314	0.094	14297	0.089	45611	0.313
Sole Proprietorship	0.329	43130	0.089	9528	0.286	52658	0.181
Self Employed	0.588	8177	0.629	628	0.591	8805	0.071
Others	0.314	5641	0.095	317	0.302	5958	0.053
Total	0.133	270432	0.133	101799	0.133	372231	0.273

Table C4-5 compares the racial group shares based on the information in the PPP loan-level data for restaurant borrowers with and without a Yelp link. The sample includes all restaurant borrowers that have non-missing race and ethnicity information in the PPP dataset. Most of the race groups have a similar share for the linked and unlinked samples, except for African American borrowers. African American borrowers are less represented in the linked sample.

Table C4-5

This table reports the racial group shares based on the information in the PPP loan-level data for all restaurant borrowers that have non-missing race and ethnicity information. We report results for borrowers with and without a Yelp link, and the entire sample.

	UnLinked	Linked	Total
White	0.488	0.570	0.509
Non-White	0.512	0.430	0.491
Hispanic	0.059	0.081	0.065
African American	0.217	0.043	0.173
Asian	0.204	0.267	0.220
Native American	0.031	0.039	0.033
Obs.	57,170	19,477	76,647

Appendix D Theoretical Matching Model Analysis

1. Additional Detailed Assumptions of the Matching Model

- We further assume that $M^m + M^{nm} > M^f + M^b$ so that some borrowing demand are not satisfied in equilibrium.
- We make the assumption that lenders do not screen borrowers directly to reflect the special case of the 100% government guaranteed loans in the PPP program.
- We assume that the payoff function is increasing in borrower's rating γ_i. The exact distribution of the ratings of matched pairs in equilibrium depends on this assumption, but not our main result that the existence of a fintech-bank and minority-non-minority double difference in rating implies that non-race-neutral factors enter the payoff function In general, the distribution of borrowers of different ratings matched with each lender will be affected by how the payoff functions depend on ratings, but the difference across racial groups will be cancelled out if the dependence is race-neutral. This is also clear in our proof of Proposition 1.
- In all scenarios, race-neutral and race-, we allow the interaction between the borrower-lender specific factor $\theta_{i,j}^{m/nm}$ and rating γ_i.

2. Equilibrium of Benchmark Race-Neutral Case

We have a unique symmetric equilibrium that fintech lenders and banks are matched with borrowers above the same threshold $\underline{\gamma}$ for the minority and non-minority groups, where $\underline{\gamma}$ is determined by

$$\delta M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m)dx + \delta M^{nm} \int_{\underline{\gamma}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx = M^f$$

$$(1-\delta) M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m)dx + (1-\delta) M^{nm} \int_{\underline{\gamma}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx = M^b$$

Where $f(\mu^m, \sigma^m)$ and $f(\mu^{nm}, \sigma^{nm})$ are the density function of the normal distribution for the minority and non-minority groups respectively.

The logic of this equilibrium is the followings. Suppose that the threshold of the rating to be matched with fintech lenders is lower (higher) than the threshold of banks, then the part between

the two thresholds will deviate to the other type of lenders. The lenders are willing to accept those borrowers because those borrowers' ratings are higher than the borrowers on their margins. In equilibrium, the market cleans at the price (utility transferred) so that no deviation of borrowers can be profitable, which pushes the thresholds of ratings to the same for both types of lenders. In other words, because the fintech lenders and banks have the same payoff function, neither type of lenders have the incentive to have a lower matching threshold than other.

In addition, as lenders are indifferent between minority and non-minority borrowers, in the limit of a large sample, the percentage is the same for minority and non-minority borrowers that are matched with the same type of lenders.

On the borrower side, because borrowers who are above the matching threshold are indifferent between fintech lenders and banks, they choose randomly between different types of lenders. In the limit of a large sample, the percentages of borrowers matched with fintech lenders (δ) and banks ($1-\delta$) depends on the relative mass of lenders and borrowers.

One important implication of the model is that a higher (lower) mean of the rating distribution results in a higher (lower) percentage of matched borrowers in equilibrium. This is because the part above the threshold is larger for a normal distribution with a lager mean. In addition, minority groups tend have a larger standard deviation. Effects of standard deviation depend on the exact parameter value as the density function of normal distribution is $\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(t-\mu)^2}{2\sigma^2}}$ where the standard deviation enters in two parts with opposite effects.

3. Race-Neutral Borrower-Lender Specific Payoff Case

In the second scenario, the payoff function depends on the rating of the borrower as well as a *race-neutral* borrower-lender specific factor $\theta_{i,j}$. We allow $\theta_{i,j}$ to interact with rating γ_i to account for borrower self-selection effect or lender-selection that is related to rating.[5]

Tech Savviness (Race-Neutral). In the race-neutral tech savviness case, we consider the possibility that higher-rated borrowers are tech savvier and therefore have a higher payoff when matched with fintech lenders than with banks. Notably, however, the tech savviness is race-neutral; the minority and non-minority borrowers of the same rating level have the same additional preference for fintech lenders to banks. We normalize the tech savviness for banks to zero. For

[5] An additional utility θ without interaction with rating levels can be seen as a degenerated case.

both minority and non-minority borrowers, $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta\gamma_i$ when matched with fintech lenders, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ when matched with banks.

The equilibrium in this setting is symmetric for minority and non-minority borrowers. Reasons are the followings. Suppose the matching threshold is higher for minority borrowers for lender *j*, then the minority borrower *k* at the margin of lender *j* would ask for higher part of transferred utility or deviate to other lenders. There would be other lenders happy to accept the minority borrower *k* since her rating is higher than the borrower at their margins and being minority does not lower the total payoff to be shared. In equilibrium, the market clears at the prices (transferred utilities) so that the matching threshold across borrower types is the same for lenders in the same type and pushes the matching threshold to the same level for minority and non-minority borrowers.

However, the matching threshold is different for fintech lenders and banks because the preference for technology that is increasing in borrower's rating level enters the payoff function directly. For a higher-rated borrower, she is willing to scarify a higher part of transferred utility when matched with fintech lenders, in return for the utility gain for technology. As a result, fintech lenders attract the part of borrowers with higher ratings and the rest are matched with banks. The market clears at the prices so that the marginal borrower is indifferent between using fintech lenders and banks.

Formally, setting the outside option of borrowers to zero, the equilibrium is given by ($\underline{\gamma_f}$, $\underline{\gamma_b}$, p_f, p_b) that are determined by,

$$M^m \int_{\underline{\gamma_f}}^{\infty} f(x, \mu^m, \sigma^m)dx + M^{nm} \int_{\underline{\gamma_f}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx = M^f$$

$$M^m \int_{\underline{\gamma_b}}^{\underline{\gamma_f}} f(x, \mu^m, \sigma^m)dx + M^{nm} \int_{\underline{\gamma_b}}^{\underline{\gamma_f}} f(x, \mu^{nm}, \sigma^{nm})dx = M^b$$

$$\underline{\gamma_f}(1 + \theta) - p_f = \underline{\gamma_f} - p_b$$

$$\underline{\gamma_b} - p_b = 0$$

Where $f(\mu^m, \sigma^m)$ and $f(\mu^{nm}, \sigma^{nm})$ are the density function of the normal distribution for the minority and non-minority groups respectively.

Result – Race-Neutral Tech Savviness. In the case where the payoff function depends on borrower's rating as well as a race-neutral additional utility gain from fintech lenders that is

increasing rating, we have a race-neutral equilibrium in terms of rating levels. Due to self-selection of higher-rated borrowers into fintech lenders, the average rating of borrowers matched with fintech lenders is higher than that for banks. This can be one explanation of the empirical evidence that fintech lenders are matched with borrowers with higher-ratings. The selection effect also implies a correlation between the relative percentage of fintech-backed and non-fintech-backed borrowers and the underlying rating distribution, which is the main difference from the purely rating-based payoff scenario. The evidence that minority borrowers are more likely to be matched with fintech lenders can be attributed to a combination of higher ratings on average for minority borrowers and self-selection of higher-rated borrowers into fintech lenders. This is because given that the matching threshold is the same for minority and non-minority borrowers, and given that fintech lenders are matched with the part of borrowers above the threshold in our model, a larger mean of the rating distribution leads to a larger matched area of fintech lenders. As the same in the benchmark case, the fact that higher matching rate (PPP loan gaining rate) for higher rated groups also exists in this scenario.

Lending Relationship (Race-Neutral). Lender preference for borrowers may also affect the equilibrium outcome. In particular, we discuss the situation that the payoff function differs for borrower-lender matches with and without previous lending relationship. We model the value of relationship in a simple way that the payoff function contains an additional utility component for borrower-lender matches with previous lending relationship. Since fintech lenders are new entrants in the SBA programs, we set the lending relationship with them to zero. In the race-neutral case, the additional value of lending relationship is the same for minority and non-minority borrowers; $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta\gamma_i$ when matched with banks with previous lending relationship, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ when matched with fintech lenders or banks without previous lending relationship.

We assume that the fraction of borrowers who possess lending relationship is the same for minorities and non-minorities. This controls for that the ex-ante difference in lending relationship accounts for the matching share differences in equilibrium. Relaxing this assumption changes the share of matches with different types of lenders, but not the average rating level of matched pairs. As we shall present in the race-biased case, in our model, the racial bias in the valuation of the lending relationship endogenously leads to an ex-post difference in the fraction of matches with

different lenders even without ex-ante difference in lending relationship across borrower racial groups.

This case is a mirror extension of the tech savviness case where the additional utility now exists for a subset of borrowers who are matched with banks. We have an equilibrium where,

$$(1-\delta)(1-\alpha)M^m \int_{\underline{\gamma_f}}^{\infty} f(x,\mu^m,\sigma^m)dx + (1-\delta)(1-\alpha)M^{nm} \int_{\underline{\gamma_f}}^{\infty} f(x,\mu^{nm},\sigma^{nm})dx = M^f \quad (D1.1)$$

$$\alpha M^m \int_{\underline{\gamma_{b,r}}}^{\infty} f(x,\mu^m,\sigma^m)dx + \alpha M^{nm} \int_{\underline{\gamma_{b,r}}}^{\infty} f(x,\mu^{nm},\sigma^{nm})dx$$
$$+\delta(1-\alpha)M^m \int_{\underline{\gamma_{b,nr}}}^{\infty} f(x,\mu^m,\sigma^m)dx + \delta(1-\alpha)M^{nm} \int_{\underline{\gamma_{b,nr}}}^{\infty} f(x,\mu^{nm},\sigma^{nm})dx = M^b \ (D1.2)$$

$$\underline{\gamma_f} - p_f = \underline{\gamma_{b,nr}} - p_f = \underline{\gamma_f} - p_b = \underline{\gamma_{b,nr}} - p_b \quad (D1.3)$$

$$\underline{\gamma_{b,nr}} - p_b = 0 \ (D1.4)$$

$$\underline{\gamma_{b,r}}(1+\theta) - p_b = 0 \ (D1.5)$$

Where $f(\mu^m,\sigma^m)$ and $f(\mu^{nm},\sigma^{nm})$ are the density function of the normal distribution for the minority and non-minority groups respectively. α is the fraction of borrowers with lending relationship with banks. $(D1.3)$ is the borrower incentive compatibility constraint that neither the marginal fintech or the marginal bank borrower (without relationship) can be better by deviate to other lenders.

$$(D1.3) + (D1.4) + (D1.5) \Rightarrow \underline{\gamma_f} = \underline{\gamma_{b,nr}} \ and \ \underline{\gamma_{b,r}} = \frac{\underline{\gamma_{b,nr}}}{1+\theta}$$

As $\theta > 0$, the matching threshold is lower for the borrowers with lending relationship with banks than for borrowers without lending relationship. Borrowers without lending relationship with banks are indifferent between using fintech lenders and banks. In the large sample limit, δ is determined by the relative mass of fintech lenders and banks (M^f and M^b).

Therefore the equilibrium is characterized as $(\underline{\gamma}, \delta)$ by solving the following equations,

$$(1-\delta)(1-\alpha)M^m \int_{\underline{\gamma}}^{\infty} f(x,\mu^m,\sigma^m)dx + (1-\delta)(1-\alpha)M^{nm} \int_{\underline{\gamma}}^{\infty} f(x,\mu^{nm},\sigma^{nm})dx = M^f \quad (D1.1')$$

$$\alpha M^m \int_{\frac{\underline{\gamma}}{1+\theta}}^{\infty} f(x,\mu^m,\sigma^m)dx + \alpha M^{nm} \int_{\frac{\underline{\gamma}}{1+\theta}}^{\infty} f(x,\mu^{nm},\sigma^{nm})dx$$
$$+\delta(1-\alpha)M^m \int_{\underline{\gamma}}^{\infty} f(x,\mu^m,\sigma^m)dx + \delta(1-\alpha)M^{nm} \int_{\underline{\gamma}}^{\infty} f(x,\mu^{nm},\sigma^{nm})dx = M^b \ (D1.2')$$

Result – Race-Neutral Lending Relationship. In the case where the payoff function depends on borrower's rating as well as a race-neutral additional utility gain from banks for the

subset of borrowers with previous lending relationship, we have a race-neutral equilibrium in terms of rating levels. Because of the additional utility from the lending relationship entering the total payoff function, the marginal borrower with relationship is of a lower rating level than the marginal borrower without relationship. This crowds out some of the higher-rated borrowers without lending relationship to fintech lenders, which provides another explanation of the empirical evidence of higher rating of the group of fintech matches. A byproduct of the crowding-out effect of lending relationship is a difference in the relative fraction between the two lender types of matched pairs for minority and non-minority borrowers if the underlying rating distributions differ.

4. Race-Biased Borrower-Lender Specific Payoff Case

Tech Savviness (Race-Biased). We start with the case that higher-rated borrowers have a higher payoff when matched with fintech lenders than with banks and this additional utility gain from technology is race-biased. We normalize the tech savviness for banks and the difference between the minority and non-minority groups when matched with banks to zero. The payoff function is $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta^m \gamma_i$ ($p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta^{nm} \gamma_i$) for minority (non-minority) borrowers when matched with fintech lenders, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ when matched with banks for both minority and non-minority borrowers.

Following the same logic as in the race-neutral tech savviness case, an additional utility when matching with fintech lenders results in a higher matching threshold of rating for fintech lenders than for banks. Unlike in the race-neutral case, the equilibrium is asymmetric in the matching thresholds with fintech lenders (i.e.,$\underline{\gamma_{mf}}$ and $\underline{\gamma_{nmf}}$ are different).

The key reasons are the followings. The incentive compatibility constraints of the marginal borrowers implies that for fintech lenders, the market clears at the prices (transferred utilities) so that the group of borrowers associated with a higher level of tech savviness (θ) are willing to pay a higher share of the total payoff to the lenders. Combined with the lender's incentive compatibility constraints that lead to an equal absolute amount of transferred utility within the same type of lenders ($p_{mf} = p_{nmf}$ and $p_{mb} = p_{nmb}$), the matching thresholds for fintech lenders are inversely related to tech savviness.

Setting the outside option of borrowers to zero, the equilibrium in the race-biased tech savviness case is given by ($\underline{\gamma_{mf}}$, $\underline{\gamma_{mb}}$, $\underline{\gamma_{nmf}}$, $\underline{\gamma_{nmb}}$, p_{mf}, p_{mb}, p_{nmf}, p_{nmb}) that are determined by

$$M^m \int_{\underline{\gamma_{mf}}}^{\infty} f(x, \mu^m, \sigma^m)dx + M^{nm} \int_{\underline{\gamma_{nmf}}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx = M^f$$

$$M^m \int_{\underline{\gamma_{mb}}}^{\underline{\gamma_{mf}}} f(x, \mu^m, \sigma^m)dx + M^{nm} \int_{\underline{\gamma_{nmb}}}^{\underline{\gamma_{nmf}}} f(x, \mu^{nm}, \sigma^{nm})dx = M^b$$

$$\underline{\gamma_{mf}}(1 + \theta^m) - p_{mf} = \underline{\gamma_{mf}} - p_{mb}$$

$$\underline{\gamma_{nmf}}(1 + \theta^{nm}) - p_{nmf} = \underline{\gamma_{nmf}} - p_{nmb}$$

$$\underline{\gamma_{mb}} - p_{mb} = 0$$

$$\underline{\gamma_{nmb}} - p_{nmb} = 0$$

$$p_{mf} = p_{nmf}$$

$$p_{mb} = p_{nmb}$$

One thing to notice regarding the fintech-minority double-difference is that the relative mass of borrowers to lenders of each type determines the position of the matching thresholds. This in turn affects the sign of the double-difference in the expected mean of ratings in Corollary 1. Next subsection presents a more detailed analysis on different cases. Here, we discuss the most real-world relevant case where fintech lenders capture a small fraction of the market for both minority and non-minority borrowers and thus $\underline{\gamma_{mf}}$ and $\underline{\gamma_{nmf}}$ are above the mean of the rating distribution. In this case, $G(x)$ is increasing in *x*, and we have a *negative* double-differences in the expected mean of ratings for matched pairs when minority borrowers have a *higher* value of matches with fintech lenders than non-minority borrowers.

Result– Race-Biased Tech Savviness. In the case where the payoff function depends on borrower's rating as well as a race-biased additional utility gain from fintech lenders, the equilibrium is asymmetry in matching thresholds. Because the racial group of borrowers who have a higher value for fintech lenders are willing to transfer a higher share of the total payoff to the lenders, yet the price the lenders can charge the marginal borrower is the same, matching threshold for fintech lenders is smaller for that group of borrowers. This implies that the racial bias in the payoff function translates into a racial-biased fintech-bank difference in the rating matching thresholds.

In the most real-world relevant case, this implies that if minority borrowers have a stronger preference for fintech lenders, we observe not only a larger share of fintech users for minority

borrowers even without differences in underlying rating distributions across racial groups but also a relatively larger minority-non-minority gap in ratings for fintech lenders than for banks. This is what we define as a negative fintech-bank minority-non-minority *Double-Difference* and does not exist in race-neutral payoff function cases. When fintech lenders capture a small fraction of the market, the double-differences in the matching thresholds is further translated into a double-differences in the expected mean of ratings for matched pairs.

Lending Relationship (Race-Biased). In this case, we study the situation where the payoff function contains an additional utility component for borrower-lender matches with previous lending relationship. Moreover, the additional utility is different for minority and non-minority borrowers. We set the lending relationship with fintech lenders to zero. The payoff function $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta^m \gamma_i$ ($p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta^{nm}\gamma_i$) when matched with banks with previous lending relationship for minority (non-minority) borrowers, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ when matched with fintech lenders or banks without previous lending relationship for both types of borrowers. Other assumptions are the same as in the race-neutral lending relationship case.

As a mirror situation of the tech savviness case, the main results are similar. The equilibrium is captured by,

$$(1-\delta)(1-\alpha)M^m \int_{\underline{\gamma_{mf}}}^{\infty} f(x, \mu^m, \sigma^m)dx + (1-\delta)(1-\alpha)M^{nm} \int_{\underline{\gamma_{nmf}}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx = M^f \quad (D3.1)$$

$$\alpha M^m \int_{\underline{\gamma_{mb,r}}}^{\infty} f(x, \mu^m, \sigma^m)dx + \alpha M^{nm} \int_{\underline{\gamma_{nmb,r}}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx$$
$$+\delta(1-\alpha)M^m \int_{\underline{\gamma_{mb,nr}}}^{\infty} f(x, \mu^m, \sigma^m)dx + \delta(1-\alpha)M^{nm} \int_{\underline{\gamma_{nmb,nr}}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx = M^b \ (D3.2)$$

$$\underline{\gamma_{mf}} - p_f = \underline{\gamma_{mb,nr}} - p_f = \underline{\gamma_{mf}} - p_b = \underline{\gamma_{mb,nr}} - p_b \quad (D3.3)$$

$$\underline{\gamma_{nmf}} - p_f = \underline{\gamma_{nmb,nr}} - p_f = \underline{\gamma_{nmf}} - p_b = \underline{\gamma_{nmb,nr}} - p_b \quad (D3.4)$$

$$\underline{\gamma_{mb,nr}} - p_b = 0 \ (D3.5)$$

$$\underline{\gamma_{nmb,nr}} - p_b = 0 \ (D3.6)$$

$$\underline{\gamma_{mb,r}}(1+\theta^m) - p_b = 0 \ (D3.7)$$

$$\underline{\gamma_{nmb,r}}(1+\theta^{nm}) - p_b = 0 \ (D3.8)$$

Where $f(\mu^m, \sigma^m)$ and $f(\mu^{nm}, \sigma^{nm})$ are the density function of the normal distribution for the minority and non-minority groups respectively. α is the fraction of borrowers with lending relationship with banks.

$$\underline{\gamma_{mb,r}}(1+\theta^m) = \underline{\gamma_{nmb,r}}(1+\theta^{nm}) = \underline{\gamma_{mb,nr}} = \underline{\gamma_{nmb,nr}} = \underline{\gamma_{mf}} = \underline{\gamma_{nmf}} = \underline{\gamma}$$

Similarly as in the race-neutral case, the matching threshold is lower for the borrowers with lending relationship with banks than for borrowers without lending relationship. In particular, it is lower for the group of borrowers with whom the value of relationship is higher. For example, if $\theta^{nm} > \theta^m$, then $\underline{\gamma_{nmb,r}} < \underline{\gamma_{mb,r}}$ .Borrowers without lending relationship with banks are indifferent between using fintech lenders and banks. The equilibrium is characterized as $(\underline{\gamma}, \delta)$ by solving the following equations,

$$(1-\delta)(1-\alpha)M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m)dx + (1-\delta)(1-\alpha)M^{nm} \int_{\underline{\gamma}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx = M^f \quad (D3.1')$$

$$\alpha M^m \int_{\frac{\underline{\gamma}}{1+\theta^m}}^{\infty} f(x, \mu^m, \sigma^m)dx + \alpha M^{nm} \int_{\frac{\underline{\gamma}}{1+\theta^{nm}}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx$$

$$+\delta(1-\alpha)M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m)dx + \delta(1-\alpha)M^{nm} \int_{\underline{\gamma}}^{\infty} f(x, \mu^{nm}, \sigma^{nm})dx = M^b \ (D3.2')$$

We have the same property as in the race-biased tech savviness case that the double differences in the matching thresholds between the minority-non-minority borrower types and fintech and bank lender types is negative if $\theta^{nm} > \theta^m$,

$$\underline{\Delta\Delta} \stackrel{\text{def}}{=} \left(\underline{\gamma_{mf}} - \underline{\gamma_{nmf}}\right) - \left(\underline{\gamma_{mb}} - \underline{\gamma_{nmb}}\right) = \underline{\gamma_{nmb}} - \underline{\gamma_{mb}}$$

$$= \frac{\underline{\gamma_{nmb}}}{1+\theta^m}(\theta^m - \theta^{nm}) \ < 0 \ if \ \theta^{nm} > \theta^m$$

In addition, the double differences in the conditional expectation of the rating level between the minority-non-minority borrower types and fintech and bank lender types is,

$$\mathbb{E}(\Delta\Delta|\cdot) \stackrel{\text{def}}{=} (1-\delta)(1-\alpha)\left[\mathbb{E}\left(x\middle|x \geq \underline{\gamma_{mf}}, \mu^m, \sigma^m\right) - \mathbb{E}\left(x\middle|x \geq \underline{\gamma_{nmf}}\right)\right] - \left[\alpha\mathbb{E}\left(x\middle|x \geq \underline{\gamma_{mb,r}}, \mu^m, \sigma^m\right) + \right.$$

$$\left.\delta(1-\alpha)\mathbb{E}\left(x\middle|x \geq \underline{\gamma_{mb,nr}}, \mu^m, \sigma^m\right) - \alpha\mathbb{E}\left(x\middle|x \geq \underline{\gamma_{nmb,r}}\right) - \delta(1-\alpha)\mathbb{E}\left(x\middle|x \geq \underline{\gamma_{nmb,nr}}\right)\right]$$

$= (1-\delta)(1-\alpha)\left[\mathbb{E}\left(x\middle|x \geq \underline{\gamma}, \mu^m, \sigma^m\right) - \mathbb{E}\left(x\middle|x \geq \underline{\gamma}, \mu^{nm}, \sigma^{nm}\right)\right] - \left[\alpha\mathbb{E}\left(x\middle|x \geq \frac{\underline{\gamma}}{1+\theta^m}, \mu^m, \sigma^m\right) + \right.$
$\left.\delta(1-\alpha)\mathbb{E}\left(x\middle|x \geq \underline{\gamma}, \mu^m, \sigma^m\right) - \alpha\mathbb{E}\left(x\middle|x \geq \frac{\underline{\gamma}}{1+\theta^{nm}}, \mu^{nm}, \sigma^{nm}\right) - \delta(1-\alpha)\mathbb{E}\left(x\middle|x \geq \underline{\gamma}, \mu^{nm}, \sigma^{nm}\right)\right]$

Suppose the underlying distribution is the same for minority and non-minority groups, i.e., $\mu^m = \mu^{nm} = \mu$ and $\sigma^m = \sigma^{nm} = \sigma$,

$\mathbb{E}(\Delta\Delta|\cdot) = \alpha\mathbb{E}\left(x\middle|x \geq \frac{\underline{\gamma}}{1+\theta^{nm}}, \mu, \sigma\right) - \alpha\mathbb{E}\left(x\middle|x \geq \frac{\underline{\gamma}}{1+\theta^m}, \mu, \sigma\right) = \alpha\left(h\left(\frac{\underline{\gamma}}{1+\theta^{nm}}\right) - h\left(\frac{\underline{\gamma}}{1+\theta^m}\right)\right)$

Where $h(x) = \frac{\varphi(x)}{1-\Phi(x)}$ is the hazard function of normal distribution and increasing in *x*.

If non-minority borrowers have a higher value for lending relationship ($\theta^{nm} > \theta^m$), $h\left(\frac{\underline{\gamma}}{1+\theta^{nm}}\right) < h\left(\frac{\underline{\gamma}}{1+\theta^m}\right)$, and thus the double differences in the conditional expectation of the rating level $\mathbb{E}(\Delta\Delta|\cdot) < 0$.

Result– Race-Biased Lending Relationship. In the case where the payoff function depends on the borrower's rating as well as a race-biased additional utility gain from banks for the subset of borrowers with previous lending relationship, the equilibrium is asymmetry in matching thresholds. Because the racial group of borrowers with a higher value for lending relationship consider the compensational gain from lending relationship larger, they are willing to transfer a relatively higher share of the total payoff to lenders. Given the utility transferred to lenders from the marginal borrower is the same, the matching threshold for borrowers with lending relationship for that racial group is smaller. That is, for the group of borrowers with a higher value of lending relationship, the lending standards in equilibrium is lower. For borrowers without lending relationship, their outside option is the same, and the matching threshold for them, in equilibrium, is the same for minority and non-minority groups, either using fintech lenders or banks.

In this case, we also have the result that the racial bias in the payoff function can translate into a racial-biased fintech-bank difference in the rating matching thresholds, which also endogenously affects the share and average rating of matched borrowers with different lenders. In reality, banks may have a higher value for non-minority borrower's lending relationship due to bias, then our model predicts that the matching threshold is lower for non-minority borrowers with lending relationship than minority borrowers with lending relationship. In observed outcomes, we see a higher relative share of matches with fintech lenders for minority borrowers, compared to matches with banks. The reason behind this is a higher fraction of non-minority-bank matches due

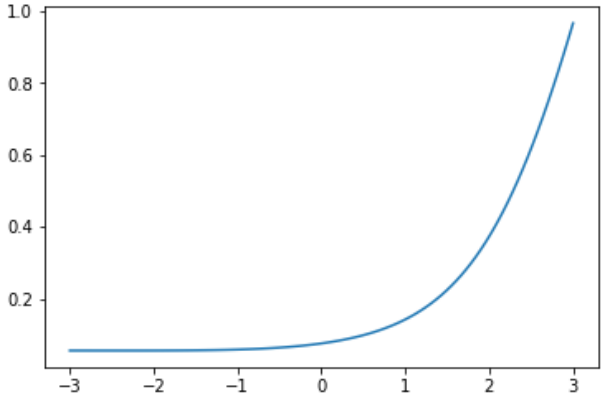
to lending relationship. In addition, we also observe a negative fintech-bank minority-non-minority *Double-Difference* in rating levels. A lower matching threshold for non-minority borrowers with lending relationship implies that the minority-non-minority gap is larger for matched pairs with banks than for pairs with fintech lenders.

5. **The key function in the race-biased tech savviness case,**

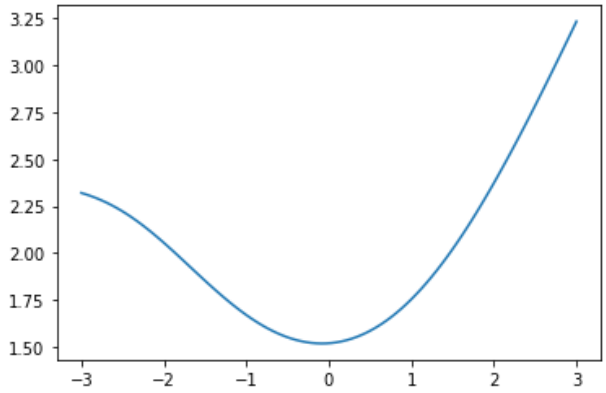
$$G(x) = \frac{\varphi(x)}{\Phi(-x)} + \frac{\varphi(x) - \varphi(\tilde{\gamma})}{\Phi(x) - \Phi(\tilde{\gamma})}$$

For normal distribution, the hazard rate $\frac{\varphi(x)}{\Phi(-x)}$ is increasing in *x*, and $\frac{\varphi(x)-\varphi(\tilde{\gamma})}{\Phi(x)-\Phi(\tilde{\gamma})}$ is decreasing in *x*. The shape of $G(x)$ depends on the value of $\tilde{\gamma}$ which is determined by the relative mass of borrowers to lenders.

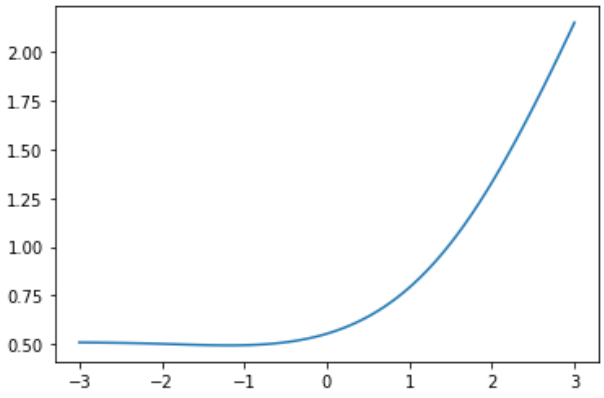
(a) $\tilde{\gamma} = 2$



(b) $\tilde{\gamma} = -2$



(c) $\tilde{\gamma} = 0.5$



(d) $\tilde{\gamma} = -0.5$

