What Drives Racial Minorities to Use Fintech Lending?

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Abstract

Using linked datasets on Paycheck Protection Program and Yelp restaurants, I document that minority-owned businesses borrow more from fintech lenders than traditional lenders. To understand the mechanisms underlying this phenomenon, I extend and estimate Schwert (2018)'s two-sided matching model between borrowers and lenders. I find that fintech-minority matches generate greater values than other matches, suggesting the taste-based discrimination of Becker (1957). Counterfactual analysis shows the importance of this value channel. Disabling this channel reduces minority borrowers' usage of fintech by approximately 70%. Disabling lending relationships and bank branch channels reduces minority borrowers' use of fintech by less than 2%.

Key Words: Fintech, Racial Barriers, Minority-owned Businesses, Paycheck Protection Program, Small Business Lending, Bank Lending, Nonbank Lending

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1 Introduction

There is substantial evidence of racial disparities in the small business credit market (Bates (1997)).[1] With the recent advent of fintech lenders (Goldstein, Jiang, and Karolyi (2019), Thakor (2020), Berg, Fuster, and Puri (2021)), there is a debate as to whether they can extend the credit provision for minorities (Fed (2021)). While the literature shows a higher fintech usage among minority than non-minority borrowers (Bartlett, Morse, Stanton, and Wallace (2022)), little evidence exists on the mechanisms underlying these inequalities. Are fintech lenders less discriminating against racial minorities? Other than discrimination, what motivates borrowers of various racial groups to choose one lender over another? And what are the magnitudes of the trade-offs between the different mechanisms? I address these questions in this paper.

Discrimination can be one explanation for racial disparities in borrowers' choice of lenders. One form is taste-based discrimination, which occurs when decision-makers exhibit a disamenity towards minority racial groups (Becker (1957)). Another form is statistical discrimination, which emerges when decision-makers use race as a proxy for unobserved credit risk (Arrow (1973), Phelps (1972)). How can fintech financing affect discrimination? On one hand, fewer in-person interactions (Buchak, Matvos, Piskorski, and Seru (2018), Fuster, Plosser, Schnabl, and Vickery (2019)) can reduce taste-based discrimination. On the other hand, lending algorithms may introduce statistical discrimination (Kleinberg, Lakkaraju, Leskovec, Ludwig, and Mullainathan (2018), Hoffman, Kahn, and Li (2018)).

In addition, the endogenous matching of borrowers and lenders permits the existence of other mechanisms.[2] Disparities in lending relationships and banking access are potential alternative channels. Evidence shows that fintech lenders substitute traditional lenders (Gopal and Schnabl (2022)), especially in areas with fewer bank branches and industries with fewer lending relationships (Erel and Liebersohn (2022)). Minority borrowers may turn to fintech even in the absence of lender discrimi-

[1] Other papers include Cavalluzzo and Cavalluzzo (1998), Cavalluzzo et al. (2002), Blanchflower et al. (2003), Cavalluzzo and Wolken (2005), Blanchard et al. (2008), Asiedu et al. (2012), Bates and Robb (2013).

[2] I thank Jeremy Stein for the suggestion of using an endogenous matching framework to study the PPP.

nation since they are more likely to unbank (Rhine, Greene, and Toussaint-Comeau (2006)). Sorting based on borrower characteristics can be another mechanism. For example, less creditworthy borrowers use fintech (Di Maggio and Yao (2021)), and minority borrowers are less creditworthy.

Because multiple mechanisms can influence the equilibrium outcome, it is essential to estimate the tradeoffs between them. I extend and estimate an empirical matching game model between the borrowers and lenders (Schwert (2018)). The first novel finding of this paper is that fintech and minority pairs generate greater matching value than other types of pairs, which suggests that the Becker (1957)'s taste-based discrimination is less severe at fintech than at banks. That is the extent to which minorities need to be more valuable is smaller at fintech than at banks. The second novel finding is that the channel on higher matching values of fintech-minority pairs is much more relevant than other channels in explaining the higher usage of fintech among minorities.

In this paper, I exploit a unique environment, the Paycheck Protection Program (PPP),[3] which is a good laboratory for three reasons. First, the Small Business Administration sets the loan terms, which precludes fintech lenders from attracting minority borrowers by offering different loan terms. Second, the Covid-19 shock hit all small businesses almost simultaneously, which controls the impact of the business development stage on fintech adoption. Third, because the Covid-19 crisis is an economy-wide shock, the interest rate is extremely low, and loan can be fully forgiven, borrowers have strong incentives to participate.[4]

Specifically, I examine the sources of racial disparities in fintech usage using a nationwide sample of 98,000 restaurants that received PPP loans linked to Yelp.com. My sample offers the following advantages. First, it enables me to construct a proxy for minority ownership using Yelp.com's cuisine category. This resolves the original PPP data limitation that race and ethnicity information is missing for about 80% of the sample. Second, in essence, all restaurants are eligible for the PPP,

[3] Paycheck Protection Program is a key component of the Coronavirus Aid, Relief, and Economic Security (CARES) Act enacted on April 3, 2020. See Cororaton and Rosen (2021), Erel and Liebersohn (2022) and Granja et al. (2022b).

[4] Admittedly, some borrowers may be rejected after submitting a loan application. This concern is mild as the survey results in Bartik et al. (2020) indicate that inability to submit an application accounts for two-thirds of loan denials. In contrast, only 8% of loan applications are rejected by the SBA.

implying that there is no regulatory variation.[5] Third, as a proxy for operational performance, the Yelp rating provides a measure to test the taste-based discrimination channel, as to be elaborated below.

Beginning with reduced-form evidence, I first demonstrate a positive and statistically significant association between minority ownership and fintech usage. In 2020, Black-, Asian-, and Hispanic-owned restaurants are 9.17%, 8.44%, and 1.22% more likely to use fintech lenders, with the sample mean being 9%. In the OLS regressions, I compare the changes in the coefficients before minority indicators with and without the observable as a control variable to determine how much various observables contribute to the variation in fintech usage. Take the Black group as an example: variations in fintech usage are explained by observed business characteristics, including *Employment Size*, *Franchise*, *Number of Ratings* and *Business Type* for 16.67%, by lending relationships for 0.55%, by the number of bank branches for 0.22%, and by across-city differences for 30.02%.

Next, I present evidence in support of the taste-based discrimination channel. I find a more negative rating gap between minorities and non-minorities at fintech lenders. This suggests that fintech lenders are less discriminatory towards minority borrowers than traditional lenders, which is consistent with Chernenko and Scharfstein (2022) and Howell et al. (2022). Consider four Massachusetts restaurants that received PPP loans as an illustration. Siam Thai (minority) has a Yelp rating of 4.1 stars, whereas Santa Maria (non-minority) has a rating of 2.6 stars. Both borrowed from the Bank of America. Jing's (minority) rating was 2.3 stars, whereas Eva's (non-minority) rating was 4.2 stars. Both borrowed from PayPal, a fintech lender. In this example, a minority restaurant must be 1.5 stars *higher* than a non-minority restaurant in order to borrow from banks. In comparison, if borrowing from PayPal, the minority-owned restaurant would be 1.9 stars *lower* than the non-minority-owned restaurant. This stark difference of a positive rating gap at banks and a negative rating gap at fintech indicates that fintech lenders counteract a 3.4-star bias against minorities.

[5]In the majority of industries, qualifying requires either meeting the SBA's size requirements for small businesses or having fewer than 500 employees. The Accommodations and Food Services sector eligibility is that each location must have fewer than 500 employees.

In addition, the finding that the racial gap is negative at fintech is consistent with the findings in Griffin, Kruger, and Mahajan (2022) that fintech lenders attract more borrowers who misreport their information. My results supplement theirs by extending from fraudulent borrowers to lower-rated borrowers. Exploring heterogeneity among lenders, I find that the four largest banks in my sample, JPMorgan, Bank of America, Wells Fargo, and U.S. Bank, do *not* have a substantial racial gap. Yet, relatively smaller banks have pronounced racial gaps. This contrast between big and small banks is consistent with the finding of Howell et al. (2022) that automation reduces racial disparities for large banks. Comparing results between years, the evidence of racial disparities is much weaker in 2021 than in 2020, consistent with the findings in Fairlie and Fossen (2022) and the increased government effort to make the PPP more effective. Results are robust when restricted to a matched sample, controlling for city$\times$month fixed effects, and controlling for approval date fixed effects.

Two caveats should be considered when interpreting the rating gap result. First, using Yelp ratings as the outcome variable instead of the default is specific to the PPP context. Default is not a major concern in PPP because the SBA provides full guarantee of all loans and forgiveness for eligible loans.[6] Instead, it is more important to consider the profitability and importance of the businesses, which have been shown to correlate with ratings (Bernstein and Sheen (2016), Luca (2016)). Second, speaking to statistical discrimination, while the government's full guarantee eliminates statistical discrimination based on credit risk (Fairlie and Fossen (2021), Howell et al. (2022)), lenders may be exposed to other risks correlated with race. In the earliest stages of the PPP, there was uncertainty about the program's requirements and a lack of bank personnel to process applications. As a result, banks were incentivized to make the most profitable use of their limited resources. My finding that the racial gap is smaller in fintechs than in banks is conditional on the risks captured by the other channels, including lending relationships, bank dessert, and business characteristics.

[6] According to the SBA, more than 95% of the loans are forgiven.

In addition, two findings are more supportive of taste-based than statistical discrimination. First, I find that while minority borrowers tend to be of lower rating, fintech users are of a higher rating on average, which would lead to the conclusion that non-minority are more likely to use fintechs under statistical discrimination based on rating. Second, I find that the loan approval date for fintech borrowers in 2020 is later than for non-fintech borrowers, which supports the argument that minority borrowers initially applied to traditional lenders, were denied, and then turned to fintech lenders.

Nevertheless, reduced-form analysis cannot provide direct information about the matching procedure. Consequently, I extend the empirical matching game model, adopted by Schwert (2018) to describe the borrower and lender matching process.[7] The empirical matching model provides a nice way to estimate racial discrimination because what the model estimates is exactly what the definition of taste-based discrimination captures. The empirical matching model can tell whether the match between fintech lender and minority borrower pairs generates a higher matching value than other types of pairs and thus whether the extent that minority borrowers need to be more valuable (i.e., taste-based discrimination) is lower at fintechs. The beauty of the empirical matching model is that it does not require data on the latent matching value, unlike in the reduced-form analysis, but it can still provide estimates of how characteristics of lenders and borrowers enter the value function.

I find a positive coefficient before the interaction term between the fintech lender and minority borrower dummies, indicating that fintech-minority pairs generate higher values than other types of lender-borrower pairs ("fintech-minority value channel"). This is consistent with taste-based discrimination, as the degree to which minority borrowers need to be "more valuable" than non-minority borrowers is lower at fintech than at banks. Coefficients are positive for the lending relationship and bank branch channels, and negative for the geographic distance channel. The

[7] I employ the Fox (2018) estimator instead of other estimators for the matching game because it does not require data on transferred utility despite the matching game model considering transferred utility between borrowers and lenders. Schwert (2018) applies the Fox (2018) estimator to the borrower-lender endogenous matching without addressing the value of fintech lenders to minority borrowers.

rating-based sorting coefficient is positive in 2020 but insignificant in 2021.

Speaking about the tradeoffs between different channels, I find that the lending relationship channel is approximately three times as important as the fintech-minority value channel in the endogenous matching game. The bank branch channel is roughly as important as the fintech-minority value channel. However, the relevance in the matching game may differ from the relevance in racial disparities in fintech usage. The counterfactual analysis reveals that the fintech-minority value channel has a remarkable and unique role in explaining racial disparities in lender selection. Shutting down this channel reduces minority borrowers' usage of fintech by approximately 70%. On the contrary, shutting down lending relationship and bank branch channels only lowers the minority borrowers' fintech usage by less than 2%. In this sense, my structural model can reconcile seemingly contradicting perspectives of lending relationships in the PPP.[8]

It might be counter-intuitive that channels on lending relationships, bank desert, and geographic distance do not explain why racial minorities use fintech lenders, especially given their great importance in the borrower-lender matching procedure per se. The reason why we do not observe racial disparities in fintech utilization change dramatically in the counterfactual analysis where we shut down these other channels is that they add to the matching value to a similar degree concerning minorities and non-minorities. My results suggest that lending relationships increase the matching value between borrowers and lenders almost equally for minorities and non-minorities.

Several contemporaneous papers present results that are consistent with mine. Erel and Liebersohn (2022) show that fintech lenders issued more PPP loans in ZIP codes with fewer bank branches and a greater proportion of minority households, as well as in industries with fewer banking relationships. Fairlie and Fossen (2022) find that minority-populated areas receive fewer PPP loans. In comparison to these papers, I find that, after controlling for lending relationships, bank branches, and geographic variation, fintech lenders lend disproportionately to minority-owned businesses. My

[8] Li and Strahan (2021), Duchin et al. (2022), Balyuk et al. (2020b) and Erel and Liebersohn (2022) show lending relationships are important in PPP while Chernenko and Scharfstein (2022) and Howell et al. (2022) show lending relationships merely explain racial disparities in PPP.

paper also complements Chernenko and Scharfstein (2022), Chernenko et al. (2022), Howell et al. (2022), and Griffin et al. (2022) by providing novel evidence that fintech lenders extend credits to lower-rated minority restaurants. Moreover, I quantify the tradeoffs between various channels in the endogenous borrower-lender matching.

More broadly, my findings contribute to the emerging literature on fintech lending in small business loans, in particular, on the financial inclusion role of fintech lenders (Jagtiani and Lemieux (2018)), the relationship with traditional lenders (Cumming, Farag, Johan, and McGowan (2021), Gopal and Schnabl (2022), Beaumont, Tang, and Vansteenberghe (2021), Donaldson, Piacentino, and Thakor (2021)), and credit supply of online lenders (Ben-David, Johnson, and Stulz (2021)). It also relates to papers on racial biases in the fintech lending process (Bartlett, Morse, Stanton, and Wallace (2022), D'Acunto, Ghosh, Jain, and Rossi (2020), Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022), Dobbie, Liberman, Paravisini, and Pathania (2021)). My paper adds to the literature by providing novel evidence on the substantial additional value of fintech lending for minority racial groups.

2 Conceptual Framework

This section discusses the various channels that can contribute to racial disparities in fintech usage. I begin by developing a simple game theory model with transferable utility, à la Azevedo and Hatfield (2018), to differentiate between the *sorting* and *taste-based discrimination* channels. The primary objective of the toy model is to demonstrate how to use observables to test for the existence of the empirically difficult-to-measure racial bias in the lender's taste. I also briefly discuss how three other channels can result in more minority borrowers using fintech lenders: prior lending relationships (Li and Strahan (2021); Duchin et al. (2022)), the bank desert (Erel and Liebersohn (2022), Wang and Zhang (2020)), and the geographic location (Granja et al. (2022b)). Due to this paper's length and empirical nature, the model does not include these three easily-integrated channels.

Model Setup. In the economy, there is a M^f mass of fintech lenders, a M^b mass of banks, a M^m mass of minority borrowers, and a M^n mass of non-minority borrowers. Consistent with the empirical patterns presented in Figure 1, I assume that the ratings of minority and non-minority borrowers follow the normal distributions, $\gamma_i^m \sim N(\mu^m, \sigma^m)$ and $\gamma_i^n \sim N(\mu^n, \sigma^n)$, respectively.

[INSERT Figure 1 AROUND HERE]

Payoff Function. The payoff of a match between borrower i and lender j, $p_{i,j}(\gamma_i, \theta_{i,j})$, is determined by the borrower's rating γ_i and a lender preference parameter $\theta_{i,j}$.[9] The parameter $\theta_{i,j}$ may be race-neutral or race-dependent, representing the taste-based discrimination channel. $p_{i,j}(\gamma_i, \theta_{i,j}) = g(\gamma_i)$ for borrowers who have been paired with traditional lenders. $p_{i,j}(\gamma_i, \theta_{i,j}) = g(\gamma_i) + h(\theta_{i,j}, \gamma_i)$ for borrowers paired with fintech lenders, where $h(\theta_{i,j}, \gamma_i)$ reflects the difference between fintech and bank preferences. I include a $\theta_{i,j}$-dependent function only for fintech lenders for the sake of simplification. As the model's most important prediction is on a relative scale, it is equivalent to including a function for both banks and fintech lenders with a different $\theta_{i,j}$ (as shown in the Internet Appendix D).

Functional Form Assumptions. $g'(\gamma_i) > 0$, indicating that higher-rated borrowers create a higher payoff. $\frac{\partial h(\theta_{i,j},\gamma_i)}{\partial \gamma_i} > 0$ because higher-rated borrowers are empirically observed to be more likely to use fintech lenders.[10] $\frac{\partial h(\theta_{i,j},\gamma_i)}{\partial \theta_{i,j} \partial \gamma_i} > 0$, reflecting that a greater preference (less disfavor, higher θ) from the lender indicates more marginal gains.

Matching Game. Without loss of generality, I study a 1-lender-m-borrower matching game.[11] The borrower i picks a lender j and offers a transferred utility (price). If the lender j accepts the borrower's application, a match (i,j) occurs. The lender receives the transferred utility, and the

[9] Since the borrower's rating is an empirically observable variable correlated with restaurant quality, I select it as the second parameter in the payoff function. If data is available, we can examine the model's key prediction using alternative quality measures.

[10] The economic explanation for why higher-rated borrowers are more likely to utilize fintech lenders may be that they are more tech-savvy.

[11] There are few instances in which a PPP borrower gained multiple loans. Less than two percent of the restaurants appear to be related to multiple loans, which are excluded from the final sample.

borrower receives the total payoff minus the transferred utility. If the lender j rejects the borrower's application, there is no match. The borrower i may apply to a different lender j or renegotiate the transferred utility to lender j. If no lender is able to accept borrower i for any utility transfer that leaves the borrower with a positive return, borrower i is unmatched in equilibrium.

Equilibrium. In a competitive equilibrium, pairwise stability states that any deviation from either the borrower side or the lender side cannot achieve a higher payoff. The transferred utilities (prices) clear the market such that for all matched pairs,

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

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

2.1 Sorting

In the first case, I examine the equilibrium in which the payoff function is race-neutral. Moreover, I assume $\theta_{i,j}$ is the same for all lenders. In this case, we have a unique race-neutral equilibrium. Those borrowers with ratings above the threshold $\underline{\gamma_f}$ are matched with fintech lenders, while those with ratings between $\underline{\gamma_b}$ and $\underline{\gamma_f}$ are matched with banks. The matching threshold $\underline{\gamma_b}$ and $\underline{\gamma_f}$ are determined by the following equations,

$$M^m \int_{\underline{\gamma_f}}^{\infty} f(x, \mu^m, \sigma^m) dx + M^n \int_{\underline{\gamma_f}}^{\infty} f(x, \mu^n, \sigma^n) dx = M^f \tag{2}$$

$$M^m \int_{\underline{\gamma_b}}^{\underline{\gamma_f}} f(x, \mu^m, \sigma^m) dx + M^n \int_{\underline{\gamma_b}}^{\underline{\gamma_f}} f(x, \mu^n, \sigma^n) dx = M^b \tag{3}$$

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

Proofs in the Internet Appendix D.

While the PPP's full government guarantee precludes statistical discrimination, sorting can be a channel that transforms the disparity in rating distribution between minority and non-minority groups into unequal fintech usage in equilibrium. Suppose fintech lenders are matched with higher-rated restaurants as in Equation 2 and Equation 3. Moreover, assuming that, on average, minority borrowers have higher ratings (i.e., $\mu^m > \mu^n$). A greater proportion of minority borrowers would use fintech lenders. Notably, compared to discrimination based on taste, the rating gap between minorities and non-minorities is identical for fintech and bank customers if we simply consider the sorting channel.

2.2 Taste-Based Discrimination

In the second case, the payoff function is race-biased. Directly measuring discrimination based on taste is difficult. Becker (1957) presents a framework for testing the existence of discrimination based on taste using equilibrium outcome variables that researchers may observe in the real world. Discrimination is when members of a minority are treated differently (less favorably) than members of a majority group with otherwise identical characteristics. Lenders hold a "taste for discrimination" if they have a disamenity value to lend to minority borrowers. Hence, minority borrowers may have to "compensate" lenders by being more valuable at a given interest rate or, equivalently, by accepting a lower interest rate for identical value. Because interest rate is fixed in PPP, so I focus on the former henceforth.

Like the benchmark case, the additional utility for fintech results in a higher matching threshold for fintech lenders than for banks. Unlike the benchmark case, the equilibrium is race-asymmetric in the matching thresholds of ratings. If minority borrowers feel less discriminated against at fintechs (and have a higher utility gain from fintechs, $\theta^m > \theta^n$), the additional value to compensate lender's dislike is lower at fintechs than at banks for the marginal minority borrower. Proposition 1 states this result.

Proposition 1. In the case where the payoff function is race dependent, the minority-non-minority rating gap at the marginal borrower is more *negative* for fintech if minority borrowers have a *higher* additional utility gain from fintech.

$$(\underline{\gamma_{mf}} - \underline{\gamma_{nf}}) - (\underline{\gamma_{mb}} - \underline{\gamma_{nb}}) < 0 \ iff \ \theta^m > \theta^n$$

$\square$

Proofs in the Internet Appendix D.

Under a scenario with limited loans such as the PPP, a rating gap at the marginal borrower indicates a rating gap of the average borrower. Corollary 1 presents this result.

Corollary 1.

Furthermore, suppose that the underlying distribution is the same for minority and non-minority borrowers, i.e., $\mu^m = \mu^n = \mu$ and $\sigma^m = \sigma^n = \sigma$, then the minority-non-minority rating gap between fintech lenders and banks in the conditional expectation of the rating levels equals $\sigma \left(G\left(\frac{\underline{\gamma_{mf}} - \mu}{\sigma}\right) - G\left(\frac{\underline{\gamma_{nf}} - \mu}{\sigma}\right)\right)$, where $G(x) = \frac{\varphi(x)}{\Phi(-x)} + \frac{\varphi(x) - \varphi(\widetilde{\gamma})}{\Phi(x) - \Phi(\widetilde{\gamma})}$, with $\widetilde{\gamma} = \frac{\underline{\gamma_{mb}} - \mu}{\sigma}$ and $\varphi(\bullet)$ and $\Phi(\bullet)$ as the density and cumulative distribution functions of the standard normal distribution respectively. $\square$

Proofs in the Internet Appendix D.

To sum up, an important empirical implication of my model is that I can test whether the payoff functions are race-dependent using the difference in the minority-non-minority rating gap between fintech lenders and banks. This is analogous to the productivity gap between minority and non-minority workers in Becker (1957).

2.3 Lending Relationships

Racial disparities in lending relationships can result in more minority borrowers using fintech lenders. Borrowers without prior lending relationships may face competition from borrowers with lending relationships from the banking system and turn to fintech lenders as an alternative option. Minority-owned businesses are more likely to be unbanked than majority-owned businesses (Rhine et al. (2006)). Additionally, as shown in Table B5 and Table B6 in the Internet Appendix, minority-owned restaurants are less likely to have previous lending relationships. In a broader context, beyond the PPP, fintech relies less on banking relationships due to its remarkable ability to deal with hard information (Balyuk et al. (2020a); Mills and Dang (2021)).

2.4 Bank Deserts

The importance of bank branch density is well-established. Firm productivity (Butler and Cornaggia (2011)) and household wealth accumulation (Célerier and Matray (2019), Agarwal et al. (2021)) are significantly affected by the user's proximity to a bank desert. In regions where banks do not have branches, access to credit is even more restricted (Cortés et al. (2020)). Since neighborhoods with a large minority population are likely to have fewer bank branches, they may rely on fintech to access financial services. In fact, Erel and Liebersohn (2022) find that in PPP, fintech lenders reach a broader borrower base while banks' branch networks remain constrained.

2.5 Borrower Locations

Access to credit is drastically different for borrowers in different geographic locations. In particular, Granja et al. (2022b) shows that, rather than assisting borrowers with the greatest needs, banks tend to target regions less negatively impacted by the pandemic in the PPP. In response, borrowers in regions underserved by the traditional banking system turn to fintech lenders (Erel and Liebersohn (2022)).

3 Data

3.1 Sample Design

The analysis in this paper relies on a linked database of loan-level information on restaurants in the Paycheck Protection Program (PPP) and the full history of customer ratings downloaded from Yelp.com. For the PPP dataset, I use the loan-level data released on March 2, 2021 (through sba.gov, FOIA), which contains detailed and comprehensive loan-level information for all sizes. The completeness of the 2021-March release of the PPP data enables me to address questions that have not been answered in early studies.[12] This completeness is crucial for my study because minority-owned businesses tend to be smaller (Fairlie and Robb (2008))) and received smaller loans (Atkins et al. (2022), Fairlie and Fossen (2021)). The entire PPP dataset contains around 6.46 million loans processed by 5,593 lenders. I restrict the sample to the *first-draw* recipients in 2020 and 2021, which refers to *first-time* loans applied for by borrowers in 2020 and 2021. For borrowers, I use the information on the business name, address, state, zip code, industry, business entity type, reported employment size, and franchise name for borrowers. For lenders, I use the information on the formal organization name, address, and zip code.

Businesses in the Food Services and Drinking Places sector (NAICS code 722) gained around 0.37 million loans (5.77%). I use both code-based searching algorithms and manual corrections for the procedure to link PPP loans to Yelp restaurants. Details in the Online Appendix C3. I exclude borrowers in Puerto Rico, Northern Mariana Islands, Guam, U.S. Virgin Islands. 101,803 loans are matched to a *meaningful restaurant-type* link on yelp.com, which accounts for 28.01% of the whole Food Services and Drinking Places sector loans.[13] The matching rate is reasonable given the strict criteria that require matching both addresses and names. By matching the PPP loan sample to a meaningful yelp link, I restrict it to a sample that is likely not fraud, as discussed in Griffin et al. (2022). Online Appendix C3 also compares the linked and unlinked samples, which shows a high similarity between the two for fintech usage and racial distributions in most cases. Admittedly, the sample under-represent businesses of sole proprietorship and African Americans. After matching to Yelp, For the purpose of this study, I further restrict to a sample consisting of 98,825 restaurant PPP recipients that are *active* from April 2018 to March 2021.

[12] Earlier studies on the Paycheck Protection Program (Erel and Liebersohn (2022), Granja et al. (2022b), Li and Strahan (2021)) use the 2020 release of the data that contains borrower names only for loans above $150,000. This paper uses the 2021 release that contains borrower-level identifiable information for loans both above and below $150,000, which allows for linking PPP loans and Yelp ratings for the full sample.

[13] The sample unlinked to Yelp consists of the following parts: a non-restaurant Yelp link, a non-business or unclear address, a large difference in the name of the restaurant and loan applicant entity, and no yelp websites.

3.2 Variable Construction

First and foremost, my analysis requires the distinction between traditional and fintech lenders, for which I mainly use the *Fintech Company List* published on the SBA official website. I supplement the official list with information from the SBA state subsidiary websites and major news sources. I identify 15 fintech lenders; the full list is in Table B2 in the Appendix.[14] In the Internet Appendix Table B4, I present the comparison between my sample and the Erel and Liebersohn (2022) sample, which further confirms the reliability of my classification. Noticeably, I do not classify all non-banks as fintech lenders because SBA lending programs feature the participation of many traditional non-bank lenders to provide funding to less bank-connected small businesses. These non-banks are similar to banks in their lending technology.[15] Details on how I identify fintech lenders are in the Online Appendix C1.

Second, it is important to identify minority-owned businesses among PPP loan recipients for a representative sample. One limitation of the original PPP data is that the information on the race and ethnicity of loan recipients is missing for almost 80% of the sample and may have selection biases in the sample containing the demographic information. To address this limitation, I use the cuisine type of the restaurant as a proxy for the race and ethnicity information of the owner. I classify restaurants into four groups: African American-, Asian- (including Pacific Islander), Hispanic-, and White-owned.[16] I cross-validate my measure of minority-owned businesses by comparing the Yelp minority dummies and the PPP minority dummies. Results are reported in Appendix Table B3. The proxy provides a reliable conservative measure in the sense that the false positive rate is reasonably low.[17]

[14] Table B2 also reports the percentage of loans included in my final sample linked with Yelp ratings, which indicates that my linked sample is evenly distributed across each fintech lender.

[15] Examples include CRF Small Business Loan Company, LLC and Hana Small Business Lending, Inc. Other papers on small business lending (Gopal and Schnabl (2022)) and the mortgage credit market (Buchak et al. (2018), Fuster et al. (2019)) also make the distinction between fintech companies and other non-banks.

[16] Some examples are African, Somali, and Soul Food as African American; Asian Fusion, Japanese, Chinese, and Pakistani as Asian; Acai Bowls, Caribbean, and Mexican as Hispanic.

[17] The concurrent literature addresses the data incompleteness of demographic information by several ways including conducting zip-code/county level analysis (Erel and Liebersohn (2022), Fairlie and Fossen (2021)), restricting to the subset of PPP recipients with demographic information (Atkins et al. (2022)), estimating the racial group based on

Third, I use the customer ratings from Yelp.com to gauge the restaurant's quality. Yelp ratings are shown to be related to revenue increase (Luca (2016)) and are used as a proxy for operational performance (Bernstein and Sheen (2016)), restaurant sales (Anderson and Magruder (2012)) and visits (Davis et al. (2019)). Importantly, Raval (2020) shows that fake reviews are less likely on Yelp compared to Google. I collect the full history of the ratings and construct a restaurant-month panel by taking the average of ratings in each month for each restaurant. A rating panel allows me to control time trends in ratings by including monthly fixed effects.

Lastly, I also merge other datasets to enrich the scope of my analysis, including additional restaurant-level information from Yelp.com, 7(a) and 504 program loan-level data from 1990 to 2019, and HUD USPS zip code crosswalk files. In addition, I classify lenders into banks, Certified Community Development Financial Institutions (CDFIs) loan funds/Certified Development Companies (CDCs), and other non-banks using information from the Federal Financial Institutions Examination Council (FFIEC). Details on the lender classification and steps to match with FFIEC are in Online Appendix C2.

In sum, details on variable definitions and data sources can be found in Table B1 in the Appendix.

3.3 Matched Sample

I use a matched sample to address the concern that borrower characteristics can simultaneously affect fintech usage and the likelihood of minority ownership. I construct the matched sample by matching minority borrowers with non-minority borrowers in the same state, business type group (aggregated), food price range, and similar size with a difference of at most five employees. When comparing the full and matched samples, I observe patterns consistent with minority-owned businesses being in a disadvantaged location and business status. Matching based on observables can account for any non-linear dependence of the outcome variable on the matching variables, thereby avoiding functional form restrictions imposed by a linear regression model.

borrower name and location (Howell et al. (2022))), and linking the PPP data with restaurant licenses and voter registrations in Florida (Chernenko and Scharfstein (2022)).

3.4 Summary Statistics

I mainly use two datasets: one restaurant-level cross-sectional dataset and one restaurant-month-level panel dataset on customer ratings. Our final sample consists of 98,825 restaurant PPP recipients active from April 2018 to March 2021. The loan and lender characteristics are observed at the PPP loan origination time; the restaurant characteristics are from Yelp.com and are observed at the time of data collection (March 2021 to July 2021).

[INSERT Table 1 AROUND HERE]

Table 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 for both the full and the matched samples. The recipients in the 2021 wave appear to differ from the recipients in the 2020 wave. For example, 32% of the 2020 recipients, as compared with 38% of the 2021 recipients, are minorities; 9% in 2020 and 17% in 2021 use fintech lenders. The average borrower in 2020 (2021) has 18.62 (9.39) employees and has a total number of 52.08 (33.01) customer reviews from April 2018 to March 2021. Overall, the 2021 wave tends to contain a larger part of financially disadvantaged borrowers than the 2020 sample.

Table 1 Panel C shows the summary statistics of rating stars in the panel dataset for the borrowers in the 2020 and 2021 waves. The ratings are pretty similar for the full and matched sample. However, the ratings are higher for the 2021 recipients than for 2020 recipients.

4 Regression Analysis

4.1 Fintech Lender and Minority Borrower Matching

I start by graphically illustrating the usage rate of fintech versus traditional lenders in the PPP program for minority- and non-minority-owned restaurants.

[INSERT Figure 2 AROUND HERE]

Figure 2 shows the daily dollar value of loans processed by non-fintech lenders (Panel A) and fintech lenders (Panel B) for minority- and non-minority-owned restaurants in the 2020 wave. Before the entry of major fintech lenders on April 10, 2020, there was an enormous gap between the dollar value of loans disbursed to minority- and non-minority-owned businesses. For example, on the first day of the program, the dollar value of loans disbursed by traditional lenders to minority-owned businesses is only 7.54% of the dollar value disbursed to the non-minority-owned businesses. In contrast, on the first day of entry, fintech lenders processed more than three million dollars of loans for minority borrowers, which amounts to about 35.96% of the dollar value disbursed to non-minority borrowers. Traditional lenders covered a relatively larger share of minority-owned businesses in the second tranche that started on April 27, 2020 than in the first tranche. However, the gap between fintech and traditional lenders is still prominent. The minority-to-non-minority ratio, measured by dollar value, is 53.38% for conventional lenders and 75.27% for fintech lenders. These results are consistent with findings using the early data release of the subsample of loans above $150,000 (Fairlie and Fossen (2021)).

Online Appendix A Figure A1 provides the figures for the 2021 wave. We still observe a smaller minority-to-non-minority ratio for fintech lenders. In the Online Appendix A Figure A2, I further decompose the minority-owned businesses into African American-, Asian-, and Hispanic-owned businesses and plot the daily disbursed dollar value by fintech and non-fintech lenders. The patterns look analogical across the three racial groups, especially after the entry of major fintech lenders, suggesting systematic patterns for higher fintech usage for all minority racial groups.

[INSERT Figure 3 AROUND HERE]

Figure 3 plots the state-level minority shares separately for fintech and non-fintech loans. Panels

A and B plot the minority share for fintech loans and Panels C and D for non-fintech loans in 2020 and 2021, respectively. The cross-state variation in the minority shares for non-fintech loans is moderate. In contrast, we observe a larger dispersion across states in minority shares for fintech loans. These results suggest that fintech and non-fintech lenders play different roles in providing credit to minority-owned businesses.

4.2 Fintech Lender and Minority Borrower Matching

In this section, I investigate the matching between fintech lenders and racial minority borrowers in a regression framework. I estimate the following specification:

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

where the main dependent variable is a dummy variable equal to one if the restaurant owner i in city c borrows from a fintech lender in the PPP program and 0 otherwise. The main independent variables, *African American*, *Asian*, and *Hispanic*, are dummy variables equal to one if the restaurant owner i is African American, Asian, or Hispanic respectively, and 0 otherwise. The omitted category is other racial and ethnic groups, mainly composed of White Americans. Standard errors are clustered at the city level.

To the greatest extent given the available data, I include the following control variables: *Employment* for business size, *I(Franchise)* for whether the business is a franchised brand, *N. Reviews* for the number of Yelp reviews of the restaurant, and *Business Type* dummies for different company organizational formats such as Corporation, L.L.C., Sole Proprietorship, and Self-Employment (details in Appendix-Table B1).

[INSERT Table 2 AROUND HERE]

Table 2 reports the results. Columns (1) and (2) present the results of the 2020 PPP for the full sample. Column (1) shows that African American-, Asian-, and Hispanic-owned restaurants have a 9.17%, 8.44%, and 1.22%, respectively, higher likelihood of using a fintech lender in the PPP. The economic magnitude is large compared to the sample mean of fintech usage (9%). Coefficients are statistically significant at the 1% level for all groups. In column (2), I control for the business characteristics described above that may partially explain the positive association between minority ownership and fintech usage. For example, employment size is shown to be an important factor in banks' decisions on borrower priority in the PPP (Balyuk et al. (2020b), Cororaton and Rosen (2021), Humphries et al. (2020)) and is very likely to be correlated with minority ownerships. Indeed, I find that one person increase in employment is associated with a 7 percent decrease in fintech usage. After controlling for variables on business characteristics, the coefficients before African American, Asian, and Hispanic dummies decrease by around 12.98%, 12.32%, and 28.69%, respectively.

Columns (3) and (4) show the results for the matched sample. The positive association between the minority dummies and the fintech dummy remains statistically significant at 1%. The economic magnitude decreases slightly, implying that the full sample results overestimate the racial disparities due to the non-linear dependence of the outcome variable on the matching covariates. Overall, all the patterns remain the same for the matched sample. Business characteristics explain around 16.66%, 14.97%, and 10.34% for African American-, Asian-, and Hispanic-owned restaurants respectively.

Columns (5) and (6) present the results of the 2021 wave for the full sample. Likewise, we observe that minority-owned businesses have a higher likelihood of using fintech lenders. The economic magnitude is larger compared to the 2020 wave but is similar if compared to the sample mean of fintech usage (17%). Results are robust when using the matched sample, as reported in columns (7) and (8). Take results using the matched sample as an example, business characteristics explain around 24.25%, 17.86%, and 10.55% for African American-, Asian-, and Hispanic-owned restaurants respectively.

Taken together, Table 2 shows that minority-owned businesses are more likely to use fintech lenders in the PPP, even after controlling for borrower characteristics including employment size, franchise, number of Yelp reviews, and business type. Taking the average of the three minority racial groups, borrower business characteristics explain around 14% in the 2020 PPP and 17.55% in the 2021 PPP.

4.3 Mechanisms

4.3.1 Lending Relationships

Racial disparities in lending relationships may be one reason why minority borrowers are more likely to utilize fintech lenders. In this section, I examine the extent to which racial disparities in lending relationships explain differences in fintech usage between minority and non-minority borrowers. Lending relationships are measured with a dummy variable equal to one if the borrower had SBA 7(a) or 504 loans between 2009 and 2019.

[INSERT Table 3 AROUND HERE]

Table 3 presents the results. Columns (1) and (2) show the 2020 PPP results for the full and matched samples, respectively. The key independent variables differ slightly in magnitude between the full and matched samples but have the same sign. Take the results of the matched sample in column (2) as an example. I find that restaurants without lending relationships are 5.62% (56.20% of the sample mean) more likely to use fintech lenders, indicating that fintech lenders provide an alternative investment tool for borrowers without lending relationships. However, when comparing column (2) in Table 3 with lending relationships as a control to column (4) in Table 2 without lending relationships as a control, the coefficients before the minority racial dummies only decrease slightly (5 -6 basis points) after controlling for lending relationships. This finding suggests that lending relationships can only partially explain racial disparities in fintech usage.

In columns (3) and (4), the 2021 PPP results exhibit the same pattern as the 2020 PPP wave. Results are also robust when using a measure of prior lending relationships based on the dollar value of 7(a) and 504 loans, as reported in the Internet Appendix Table B7.

Taken together, I find that borrowers without lending relationships are more likely to utilize fintech lenders. However, lending relationships merely explain the racial differences in the borrower's preference between fintech and non-fintech lenders.

4.3.2 Bank Deserts

In addition to lending relationships, the density of bank branches in the region of small businesses also contributes to the unbanked population. Minority-owned businesses are more likely to be located in regions with limited financial resources ("bank deserts"), which can compel them to rely on fintech lenders. In this subsection, I examine how much of the racial disparities in fintech usage can be attributed to the bank desert channel. I calculate bank branch density by counting the number of branches in the restaurant's zip code.

[INSERT Table 4 AROUND HERE]

Table 4 reports the results. Columns (1) and (2) show the results for the 2020 PPP for the full and matched samples. *N. Branches* can explain very little of the racial disparities in fintech usage. Take Column (2) as an example where the analysis uses a matched sample; after controlling for *N. Branches*, the coefficients before the minority racial dummies decrease only slightly (1 - 5 basis points). Columns (3) and (4) show the results for the 2021 PPP wave for the full and matched samples, which show the same pattern as the 2020 PPP wave.

Taken together, similar to the lending relationship channel, I find that borrowers in the bank desert have greater racial disparities in fintech usage. However, the bank desert channel only partially explains the observed racial differences, which also mirrors the finding on lending relationships.

4.3.3 City Location

Lastly, I investigate the extent to which the restaurant's location can account for racial disparities in fintech usage. I include city fixed effects to control for time-invariant variations in local economic and financial conditions that influence borrowers' choice between fintech and traditional lenders. The estimates capture the racial disparities among city residents who borrow from different lenders.

[INSERT Table 5 AROUND HERE]

Table 5 reports the results. Columns (1) and (2) show the 2020 PPP results for the full and matched samples. City fixed effects explain a large portion of the racial disparities in fintech usage. Compare the coefficient in column (2) of Table 4 without city fixed effects to the coefficient in column (2) of Table 5 with city fixed effects. The coefficient for African Americans decreases by 30.02% (using the baseline coefficient in Table 2 as the denominator). Likewise, the coefficient for Asians decreases by 12.15%. The coefficient before Hispanic becomes negligible and statistically insignificant. The substantial reduction in the coefficients' economic magnitude and statistical significance when controlling for city fixed effects suggests that, to a large extent, the higher likelihood that minority-owned businesses use fintech lenders is due to regional variation.

Columns (3) and (4) report for the 2021 PPP. In the 2021 wave, cross-city variation plays an even larger role. Based on the results of matched sample in column (4), city fixed effects explain 44.20%, 30.09%, and 19.82% of the racial disparities in fintech usage for African Americans, Asian- and Hispanic-owned restaurants, respectively. Compared to the sample mean, the remaining racial disparities in fintech usage are smaller in the 2021 wave than in the 2020 wave, indicating that non-geographic racial disparities in the lending process are reduced in the 2021 wave.

After controlling for city fixed effects, coefficients before minority racial group dummies remain positive and significant in 2020 and 2021. These results suggest racial disparities in access to the credit market both between and within cities.

Table 6 summarizes how much do different control variables explain racial disparities in fintech usage in the OLS regression format where more than half cannot be explained by observed variables. My finding that business characteristics and location account for approximately 50% of the racial disparities in fintech usage is consistent with the evidence from Chernenko and Scharfstein (2022) (their estimate is around 60%). My analysis differs from theirs in terms of sample and the outcome variable.[18] In addition, my finding that lending relationships and bank branch access only account for a small portion of racial disparities is consistent with the results of Howell et al. (2022). Another finding worth noticing is the negative coefficient before the interaction terms between lending relationships and minority racial dummies. This result indicates that fintech lenders serve as a more prominent alternative to lending relationships for minority borrowers.

4.3.4 Becker's Taste-Based Discrimination

Previous sections demonstrate that observable variables cannot explain a substantial proportion of racial disparities in the use of fintech. One reason for this large portion of unexplained racial disparities could be discrimination in tastes toward minority borrowers. Using the framework of Becker (1957), I examine whether we observe taste-based discrimination in the PPP in this section. When comparing banks and fintech, the question is whether minority borrowers need to be rated higher to compensate for lenders' disutility towards them.

The empirical analysis in this section is akin to the Difference-in-Differences method. I compare how the rating gap between minority and non-minority groups differs between fintech and non-fintech lenders. Thus, I address first-difference concerns, such as that minority borrowers are disproportionately affected by the pandemic or that fintech lenders are easier to use for all borrowers.

I estimate the following specification:

$$\text{Rating}_{i,t} = \beta I(\text{Fintech})_i \times I(\text{Minority})_i + \delta I(\text{Fintech})_i + \delta I(\text{Minority})_i + \gamma X_i + \mu_{c,t} + \varepsilon_{i,c,t}$$

[18] Their sample consists of PPP-recipient and non-PPP-recipient restaurants in Florida, whereas I use a national sample of PPP-recipient restaurants. While they study PPP take-up rate, I examine fintech usage.

The dataset is a restaurant-month panel where the dependent variable is the monthly average of customer ratings for a given restaurant from April 2020 to March 2021 (i.e., during the Covid crisis). The key independent variable is the interaction terms between the fintech indicator and the three minority racial group indicators. The coefficient beta captures the differences in the minority-non-minority rating gap between the fintech and non-fintech lenders. If minority borrowers are not less discriminated by fintech lenders, the coefficient would be statistically insignificant. I control for the fintech and racial group indicators and borrower characteristics, which are all time-invariant variables. I account for within-restaurant correlation in errors by clustering at the restaurant level.

[INSERT Table 7 AROUND HERE]

Table 7 reports the results. Columns (1) through (4) present the results for the 2020 wave. In column (1), the rating difference between African American-owned and non-minority-owned restaurants is 0.25 stars (6.4% of the sample mean) more negative for fintech borrowers than non-fintech borrowers. This finding suggests that the extent to which African American borrowers needed to be more valuable to "compensate" for lender disfavor is less when matching with fintech lenders, consistent with fintech lenders being less discriminative. Similarly, the rating gap between Asian-owned and non-minority-owned restaurants is 0.06 stars (1.5% of the sample mean) more negative for fintech borrowers than non-fintech borrowers. After controlling for city fixed effects in column (2), the coefficient before the interaction term with African Americans is reduced by 8%, while the coefficient with Asians is reduced by 33%. This magnitude decrease after controlling for city-fixed effects is consistent with the findings in Table 5. The findings for Hispanic-owned restaurants are insignificant, consistent with the findings in Table 5. The results of the matched sample are similar to those of the full sample in columns (3) and (4).

Columns (5) through (8) report results for the 2021 wave. Results for the 2021 PPP are overall less significant. The coefficients before the interaction terms between the fintech and racial group indicators for restaurants owned by African Americans and Asians become insignificant.

However, the coefficients before the interaction terms are significant and negative for Hispanic-owned restaurants. For instance, column (5) shows that the rating gap between Hispanic- and non-minority-owned restaurants is 0.18 stars (4.6% of the sample mean) more negative for fintech borrowers than for non-fintech borrowers. One possible explanation for the difference between the 2020 and 2021 PPP is that most African American and Asian borrowers who were excluded by traditional lenders already participated in the PPP program in 2020 using fintech, and thus the additional participants in the 2021 wave via fintech lenders are comparable between minority and non-minority groups. In 2021, an increasing number of Hispanic borrowers who were overlooked by traditional lenders in 2020 applied with fintech lenders.

Internet Appendix Table B8 presents the results on regressions on separate subsamples of fintech and non-fintech borrowers. I find that the minority-non-minority rating gap is less negative for non-fintech lenders, which is consistent with non-fintech lenders posing higher racial barriers than fintech lenders.

In addition, I explore heterogeneity among lenders by running the same regression specifications as in Table 7 but using a series of dummies for each lender. I focus on the four biggest fintech lenders, Cross River Bank, Kabbage, Square, and Paypal, and the seven largest banks, JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank.[19]

[INSERT Figure 4 AROUND HERE]

Figure 4 shows the results for the largest minority group in our sample: Asian-owned restaurants. Panel (a) reports results on the 2020 wave. Consistent with the pooled-lender regression results, the Asian-non-minority rating gap is negative for the fintech lenders, except being slightly positive for Cross River Bank, indicating lower barriers to using fintech lenders for minority-owned businesses.

[19] I set the threshold of big lenders where each lender covers at least 1% of the observations in our restaurant-month panel dataset of ratings. Cross River Bank, JPMorgan, Bank of America, and Wells Fargo each cover about 2.20%, 4.74%, 6.96%, and 4.26%, respectively, of the observations, and other lenders cover a share of 1%-2% of the observations per lender.

In contrast, banks tend to have positive racial discrimination, especially for smaller banks. The rating gap is positive and large for relatively "small" big banks. For the biggest three banks, JPMorgan, Bank of America, and Wells Fargo, the minority-non-minority rating gap is either not significantly different from zero or small, suggesting that big banks provide credit to a similar group of minority- and non-minority-owned restaurants in terms of their ratings. Given that big banks are likely to have better online lending platforms, this difference between big and small banks supports the argument that the automated lending process reduces the racial discrimination in small business lending (Howell et al. (2022)).

Panel (b) reports results on the 2021 wave for the Asian-non-minority rating gap. We observe no clear difference between fintech lenders and banks. This aligns with the pooled-lender regression results, which implies an improvement in 2021 in racial disparities in the program. Patterns for African Americans are shown in Panels (c) and (d), similar to the Asians. Patterns for Hispanics are shown in Panels (e) and (f). In the 2020 wave, fintech lenders do not show lower racial discrimination toward Hispanics, but they do in the 2021 wave, consistent with the different patterns for the racial disparity result in the previous section.

Taken together, findings in Table 7 suggest that fintech lenders features less significant taste-based discrimination. The consistency in results between Table 5 and Table 7 supports that the part of racial disparities unexplained by observables are due to taste-based discrimination. Overall, my findings suggest that fintech lenders are more inclusive of minority borrowers.

4.3.5 Sorting

Another potential channel discussed in section 2 is sorting based on ratings. Sorting can be a mechanism contributing to racial disparities in fintech usage only if both the fintech-rating and minority-rating relationships are of the same sign. However, in the 2020 wave, fintech users have higher ratings on average but minority borrowers have lower ratings on average (African-American-owned restaurants have higher ratings, but the coefficients are insignificant in most cases). In the

2021 wave, while we observe positive correlation between fintech usage and ratings and minority ownership and ratings (for African-American- and Asian-owned restaurants), both correlations are indistinguishable from zero. Overall, my empirical findings do not support sorting as being the channel of racial disparities in fintech usage.

4.4 Loan Approval Speed

Another explanation is the timing of loans may coincide with fintech usage. Suppose minority borrowers are less patient and prefer quicker loan processing, then they are more likely to use fintech.[20] In addition, fintech lenders are introduced later in PPP.

[INSERT Table 8 AROUND HERE]

Table 8 presents the regression results comparing the variance in the number of days required to obtain a loan approval for minority and non-minority borrowers matched with fintech and non-fintech lenders. The calculation of the gap begins on April 10, 2020, to account for the fact that fintech lenders only joined PPP after that date. In the 2020 wave, the coefficients before the interaction terms between minority racial groups and fintech indicators are insignificant for African American- and Hispanic-owned restaurants. The coefficients are positive and statistically significant at the 1% level for Asian-owned restaurants. This result is consistent with the claim that minority borrowers first applied to traditional lenders, were denied, and then turned to fintech lenders. In contrast, in 2021, minorities wait less when using fintech.

Internet Appendix Table B15 reports results where I control for the approval date fixed effects as the robustness check of Table 5 and Table 7. This estimates the minority-non-minority rating gap for loans approved on the *same* day, and thus rules out differences due to the borrower's position in the PPP application queue. Coefficients before the interaction terms between the racial group

[20] The existing literature documents that fintech lenders process mortgage applications much faster than other lenders (Fuster et al. (2019)). Internet Appendix Table B12 shows that, on average, fintech lenders have a higher loan processing capacity.

and fintech indicators are very close to those reported in Table 7, which implies that the racial discrimination does not come from a difference in loans approved earlier or later.

4.5 Other Lender Types

One concern is that non-technology-related features of fintech lenders coincidentally lead to my empirical findings. In this section, I study five other types of lenders: first-time banks, non-federally-insured lenders, credit unions, and community development financial institutions (CDFIs) and community development corporations (CDCs). If the documented minority-non-minority gap is due to unobserved characteristics of borrowers and lenders (and not due to racial barriers), we should observe the same patterns when comparing those types of lenders with the rest of lenders as for the comparison between fintech lenders and banks. Results are in Internet Appendix Table B9 to Table B12. For all alternative lender classifications, I do not find evidence similar to the fintech-bank classification.

5 Empirical Matching Model

In this section, I extend the empirical matching model of Schwert (2018) and use the game-theory-based matching estimator developed by Fox (2018) to estimate each channel's contribution to the matching value. The empirical matching model estimation complements the regression analysis in two ways. First, it estimates trade-offs between various channels, whereas the regression approach describes data correlations. Second, it can generate counterfactual matching assignments that tell us what would occur if fintech lenders did not provide additional value to minority borrowers.

Fox (2018) is the first to empirically estimate a many-to-many matching game with transferable utility, with an application in the automobile industry. Chen and Song (2013) and Schwert (2018) apply the Fox (2018) estimator to the borrower-lender matching setting in order to investigate the role of size, geographical distance, and lending relationships. My paper differs from theirs by estimating the value of fintech lenders to minority racial groups using the model.

The empirical matching model provides a nice way to estimate racial discrimination because what the model estimates is exactly what the definition of taste-based discrimination captures. The empirical matching model estimates how different characteristics of lenders and borrowers affect the latent matching value. In the particular case of this paper, it can tell whether the match between fintech lender and minority borrower pairs generates a higher matching value than other types of pairs. If the fintech-minority pairs generate higher matching values, it implies that the extent that minority borrowers need to be more valuable is lower at fintechs, which means the taste-based discrimination is lower. The beauty of the empirical matching model is that it does not require data on the latent matching value, unlike in the reduced-form analysis, but it can still provide estimates of how characteristics of lenders and borrowers enter the value function.

5.1 The Model

5.1.1 Model Setup, Equilibrium and Advantages

The empirical matching model uses the observed matching assignment as the outcome to be explained and estimates the latent matching value function, also known as the payoff function in game theory. The estimation is based on the *Revealed Preference* principle, which states that more valuable matches are likely to occur in the data. To illustrate, suppose agents always favor high-valued matches over low-valued matches. In equilibrium, agents only form matches when both sides are unable to choose a higher-valued alternative. This equilibrium condition implies that the sum of matching values of pairs observed in the data should be greater than those of unmatched pairs.

One advantage of the Fox (2018) estimator is that it considers the interactions between players in the matching game. Other matching probability estimators, such as Probit or Logit models, assume that each player's matching probability is unaffected by other players in the game. In formal terms, the equilibrium concept is known as *Pairwise Stability*, which means that no pair of agents find it advantageous to break their existing matches to match each other. Pairwise stability implies total stability under substitutable preferences (Hatfield and Kominers (2010)).

Another advantage of the Fox (2018) matching estimator is that the model accounts for transfer payments in the equilibrium condition without requiring data on the payments (loan prices), which is crucial in my context. Loan prices in the matching game include not only the prices paid by the borrower to the lender for pairs that have been matched in reality but also the *would-be* loan prices between borrowers and lenders who have not been matched in reality. While the government sets the interest rate for the PPP program, non-price loan terms can transfer value as well. In particular, a substantial portion of the utility associated with race-dependent frictions is likely to be non-financial. Other matching models either assume no transfer payments between agents (Sørensen (2007)) or require information on transferred payments (Akkus et al. (2016)). The multinomial choice model also requires information on transferred payments (Berry et al. (2004)).

5.1.2 An Illustrative Example

Consider two loans from my sample to demonstrate how the estimator Fox (2018) works. Santa Maria Atlas Pizza, a non-minority-owned restaurant in Massachusetts, borrowed from Bank of America. Jing's Garden, a minority-owned restaurant also located in Massachusetts, borrowed money from PayPal. The model compares the total latent value of the observed matches to the total latent value of the swapped matches that pair Santa Maria with PayPal and Jing's with Bank of America. [21]

For a formal description of the model, consider the match between borrower b and lender l. The match (b, l) provides utility $V_b(b, l) - t(b, l)$ to the borrower and $V_l(b, l) + t(b, l)$ to the lender, where $t(b, l)$ is the unobserved transfer payment from borrower b to lender l, which can be positive or negative. The total matching value is given by $V(b, l) = V_b(b, l) + V_l(b, l)$. Given that utility is additively separable, so the entire set of PPP loans of the lender is worth $V_l = \Sigma_{b\in\mu(l)} V_l(b, l) + t(b, l)$. As shown in Fox (2018), summing the pairwise stability conditions for two matches (b_1, l_1) and

[21] In the complete model, estimation of the matching value function involves swapping every observed pair of borrower-lender matches and maximizing the number of satisfied comparisons, not just the pair in the illustrative example.

(b_2, l_2) yields a condition that does not depend on transfer payments:

$$V_l(b_1, l_1) + t(b_1, l_1) + V_b(b_1, l_1) - t(b_1, l_1) \geq V_l(b_2, l_1) + t(b_2, l_1) + V_b(b_1, l_2) - t(b_1, l_2)$$
$$V_l(b_2, l_2) + t(b_2, l_2) + V_b(b_2, l_2) - t(b_2, l_2) \geq V_l(b_1, l_2) + t(b_1, l_2) + V_b(b_2, l_1) - t(b_2, l_1)$$

$$\Rightarrow V_l(b_1, l_1) + V_l(b_2, l_2) \geq V_l(b_2, l_1) + V_b(b_1, l_2) \tag{4}$$

The simple calculation above illustrates how transfer payments cancel out in equilibrium, and we need only compare the *total* surplus of observed and counterfactual matching pairs. Even though the pairwise stability condition involves transfer payments between the borrower and the lender, Fox (2018) achieves no transfer payment data requirements by demonstrating that estimating the equilibrium is equivalent to estimating the e*sum* of latent matching values under additively separable utility.

5.1.3 Key Assumptions

The Fox (2018) model relies on several assumptions that merit discussion. First, as described previously, the model is based on the *Revealed Preference* assumption, which states that the observed matching assignment produces the highest total value. One caveat is that there may be multiple equilibria, whereas the observed matching outcome is only one equilibrium. Multiple equilibria are most likely to exist when borrowers and lenders can negotiate over the loan terms (transfer payments). Because the interest rate and other loan terms are determined exogenously by the SBA, this concern is minimal in the PPP setting.

Second, an important assumption for the estimator to be consistent is that the model only uses all possible matches *within* the existing loan market. Since the PPP program has strict lender eligibility and capacity restrictions, this is a reasonable assumption for my application. Importantly, to account for the fact that borrowers did not consider all banks to be very far away from them, and because the Fed's PPP Liquidity Facility was established expressly to loosen bank capacity constraints

(Anbil et al. (2021)), I impose the restriction, when constructing counterfactual lender-borrower pairs, that the lender must have made at least one PPP loan in the same city as the borrower. Nevertheless, one implication is that the matching value function is collectively determined by the borrower and lender-determined characteristics, which implies that any individual borrower or lender characteristics cancel out in the equilibrium condition (Equation 4).

Third, the equivalence between pairwise stability and Equation 4 assumes that lenders have a capacity constraint, with each lender distributing the same number of loans under all counterfactual matching assignments. This assumption is also reasonable for my application in light of the anecdotal evidence of lenders reaching their capacity limits in the PPP.

Fourth, the assumption of additively separable utility entails the absence of diversification benefits, which are likely to be negligible in the PPP context due to the complete government guarantee nature of the program. Finally, the model also assumes that the borrower and lender attributes in the matching value function are unaffected by the matching outcome. The fintech lender indicator and minority borrower indicator are immutable characteristics. The previous lending relationships and geographic location of borrowers and lenders are also predetermined characteristics.

5.1.4 Maximum Score Estimator

To estimate the model, I parameterize the matching value as a linear function, $V(b,l) = X'_{b,l}\beta + \epsilon_{b,l}$, where $X_{b,l}$ includes characteristics of the borrower and lender pair. The objective function is a sum of indicators for the satisfaction of the pairwise value comparison (inequalities in the terminology of Fox (2018)):

$$Q(\beta) = \Sigma_{n=1}^{N} \Sigma_{(b_1,l_1),(b_2,l_2)\in\mu_s} \mathbf{1}(X'_{b_1,l_1}\beta + X'_{b_2,l_2}\beta \geq X'_{b_1,l_2}\beta + X'_{b_2,l_1}\beta) \tag{5}$$

which is a maximum score estimator (Manski (1975)). A global optimizer is required since the objective function is a step function. I employ the differential evolution algorithm to optimize the estimator, as suggested in Fox (2018) and adopted in Schwert (2018). I use the Python scipy differential evolution package. In order to avoid getting stuck in local optima, the differential evolution optimization incorporates randomness into the initialization step. This optimization procedure gives the point estimates of the matching model.

Regarding confidence intervals, the literature shows that bootstrapping is inconsistent for the maximum score estimator, whereas subsampling provides a consistent estimator (Delgado et al. (2001), Abrevaya and Huang (2005)). In accordance with Fox (2018), I generate confidence intervals by randomly selecting 100 subsamples and utilizing the corresponding percentiles of parameter distributions. I use block subsampling to preserve the interactions, in reality, more precisely. Each random subsample consists of 90% of the borrowers and their observed and potential lenders.[22] When confidence intervals do not contain zero, coefficients are considered statistically significant.

More details on setting up the empirical matching model can be found in Internet Appendix E.

5.2 Estimating the Matching Model

[INSERT Table 9 AROUND HERE]

Table 9 reports estimates of the matching model. Results are consistent with the results of the regression analysis. The positive coefficient on the interaction between the fintech lender and minority borrower indicators indicates that fintech lenders and minority borrowers generate greater value than other types of pairs. Consistent with previous research, borrowers and lenders with previous loans, more branch access, and a closer location are more likely to match. Consistent with the regression results in Table 7, restaurants with higher ratings are matched with fintech lenders in 2020, and the sorting pattern becomes negative and insignificant in 2021.

All parameter estimates on the 2020 PPP sample are statistically significant at the 95% confidence level. Only the coefficients on lending relationships and bank branch channels remain statistically significant at the 95% level in 2021. Other coefficients become insignificant. The difference

[22] Schwert (2018) demonstrates that block subsampling yields a larger confidence interval than direct subsampling of inequalities; consequently, the results presented in the paper should be viewed as a conservative estimation of the confidence intervals.

between 2020 and 2021 suggests that the lending relationship and bank desert are channels influencing the matching value held in broader contexts. In contrast, other channels may be more significant in scenarios with limited resources, like the 2020 PPP.

Comparing the coefficients reveals the relative importance of the various channels in the matching process. Because the matching value is arbitrarily scaled, interpreting the magnitude itself is meaningless. Instead, I discuss the ratio of different coefficients here. The fintech-minority additional value channel is comparable to the lending relationship and bank desert channels. The additional value channel is 0.33 times as important as the lending relationship channel and 0.98 times as important as the bank desert channel, according to the 2020 PPP. In accordance with the regression analysis results, the relative importance of the additional value channel of fintech-minority matches falls to 0.26 times that of the lending relationship channel and 0.41 times that of the bank desert channel in the 2021 PPP.

The geographic distance channel is of minor relative significance, consistent with the argument that information asymmetry, which tends to be affected by distance (Agarwal and Hauswald (2010), Granja et al. (2022a)), does not play a significant role in the PPP because the government backs all loans. Given the large number of inequalities, the model's fit is surprisingly satisfactory.[23]

5.3 Counterfactual

In this section, I conduct counterfactual analyses to quantify the contribution of various channels to racial disparities in fintech usage rates. For instance, I set the parameter of the fintech-minority value channel to zero and measure the impact of the predicted matching assignment on minority and non-minority borrowers' use of fintech. [24]

[INSERT Table 10 AROUND HERE]

[23] Because there are fewer counterfactual pairs in smaller samples, they tend to have better fits.

[24] Due to the possibility of ties in matching values, for each counterfactual assignment, I generate 100 random assignments for the tied ones and compute the average fintech usage rates of the 100 assignments.

Table 10 provides estimates of the impact of matching on fintech utilization for each alternative scenario. As a simple starting point, the first line indicates that randomly matching borrowers and lenders would result in a similar proportion of minorities and non-minorities using fintech lenders. In 2020, 7.80% of minority and 7.3% of non-minority borrowers would use fintech lenders under random assignments. Therefore, it is unlikely that the higher rate of fintech usage among minority borrowers is a result of random assignments.

The counterfactual of interest is shutting off the additional matching value channel for fintech-minority pairs. Suppose that matching fintech lenders with minority borrowers produces no additional value. In this counterfactual scenario, 5.82% of minority borrowers and 8.22% of non-minority borrowers would use fintech lenders in 2020, representing a 69.41% decrease in minority fintech usage and a 214.15% increase in non-minority fintech usage relative to the status quo. Additionally, reversing the sign of the parameter for this channel would reduce minority fintech usage and increase non-minority usage in a larger magnitude.

However, shutting off channels on lending relationships, bank desert, and geographic distance has minimal effects on minority versus non-minority fintech usage (the changes in the racial gap in fintech usage are less than 3.5 percent of the original racial gap). If the rating-based sorting channel were disabled, there would be 6.20 percent more minority borrowers and 23.91 percent fewer non-minority borrowers using fintech. This result is consistent with the positive correlation between ratings and fintech usage and the negative correlation between minority borrowers and ratings, suggesting that rating-based sorting discourages some minority borrowers from using fintech lenders. Results on the 2021 PPP have the same signs and relative magnitudes.

The counterfactual analyses demonstrate that the fintech-minority value channel has a unique and significant impact on racial disparities in fintech use. The fintech usage gap between minorities and non-minorities would decrease by approximately 110% if this channel were disabled. Shutting off channels on lending relationships, bank desert, and the geographic distance does not significantly alter racial disparities in fintech utilization.

It might be counter-intuitive that channels on lending relationships, bank desert, and geographic distance do not explain why racial minorities use fintech lenders, especially given their great importance in the borrower-lender matching procedure per se. The reason why we do not observe racial disparities in fintech utilization change dramatically in the counterfactual analysis where we shut down these other channels is that they add to the matching value to a similar degree concerning minorities and non-minorities. For example, my results suggest that lending relationships increase the matching value between borrowers and lenders almost equally for minorities and non-minorities.

5.4 Discussion

Last but not least, while I mainly interpret the racial gap in matching value as taste-based discrimination, there is a broader interpretation that the racial gap in matching value implies racial-based friction in the matching process. Such friction can come from both the lender and the borrower side.[25] However, most borrower-side friction can be considered rooted in taste-based discrimination. For example, the most common borrower-side racial-based friction is the expectation of being discriminated against. A minority borrower might be more concerned about being rejected from banks than my non-minority counterparts. Yet, the main reason that minority borrowers have a higher expectation of being discriminated against is their past experience of being discriminated against by the banks. In this sense, either borrower- or lender-side racial-based friction arises from taste-based discrimination.

6 Conclusion

I provide novel evidence on what contributes to racial disparities in fintech usage. Using the Paycheck Protection Program as a laboratory and a linked dataset on PPP loans and restaurants on Yelp.com, I find that minority borrowers are more likely to use fintech lenders and observable only accounts for a small fraction of the economically large racial disparities, which is consistent with

[25] I thank Samuel Rosen (discussant) for pointing this out.

contemporary papers (Chernenko and Scharfstein (2022), Erel and Liebersohn (2022), Howell et al. (2022)). With estimates of the tradeoffs between various channels, we can determine where to prioritize efforts to minimize racial disparities with greater precision. One reason for this large unexplained part of racial disparities could be taste-based discrimination (Becker (1957)) which is indicated by my rating-gap evidence.

With regard to external validity, this paper uses a nationwide sample of restaurants. The large geographic range of the sample mitigates concerns about biases due to the sample selection. On the one hand, the Food Services and Drinking Places sector has a similar degree of racial diversity to the average of all industries according to the U.S. Bureau of Labor Statistics. This suggests that our results are likely to provide insights into other sectors as well. On the other hand, restaurants are likely to have fewer collateral and assets, and thus the lending relationship channel plays a more important role.

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 government-guaranteed loan programs. Our findings suggest that there are systematic biases and blind spots in the traditional loan distribution channel 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. In addition, the impact of the introduction of fintech lenders on traditional lenders is also a promising avenue for future research.

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Figure 1: Distribution of Restaurant Ratings across Borrower Racial Groups

This figure plots the density of restaurant ratings for each racial group using data on customer ratings from Yelp.com. For each restaurant in our linked sample, we calculate the mean of the monthly average of ratings from April 2018 to March 2021.

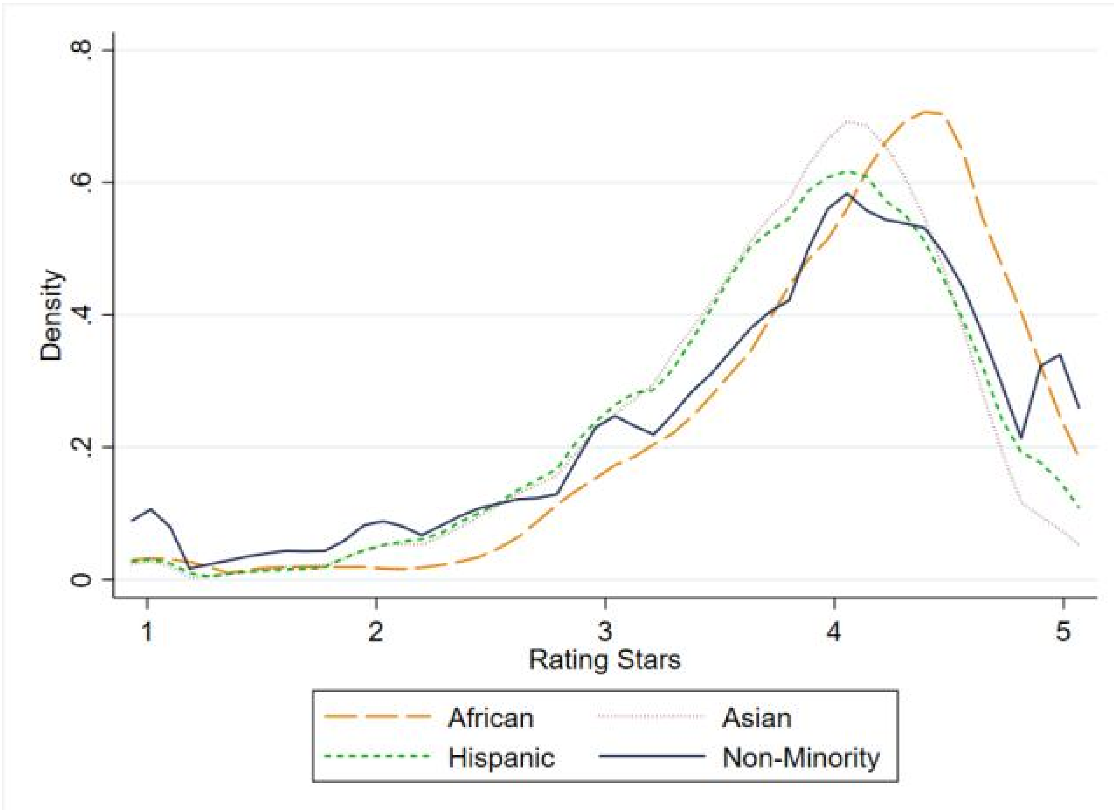
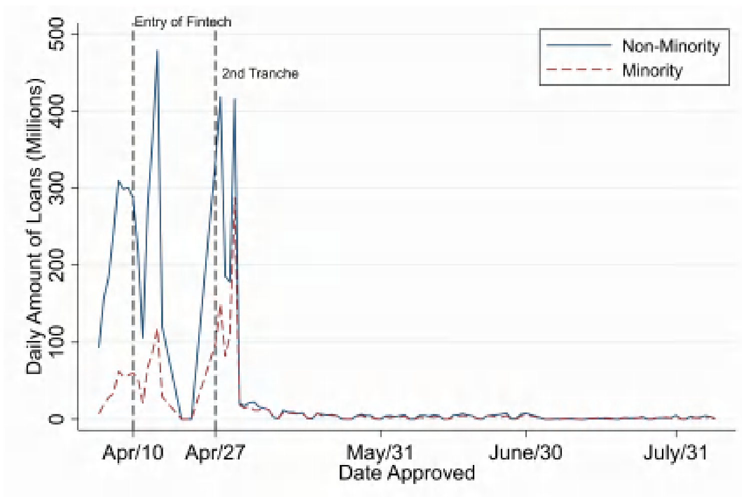
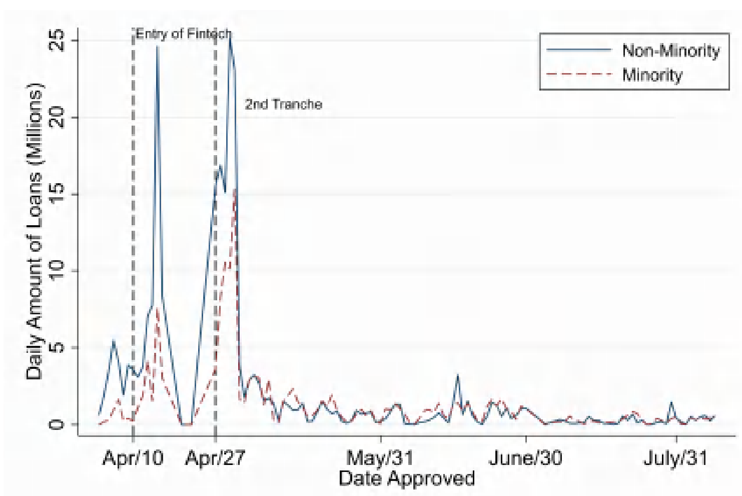


Figure 2: Minority- and Non-Minority-owned Businesses in the 2020 PPP Fintech vs. Non-Fintech (Dollar Value)

This figure plots the daily dollar value of PPP loans received by minority- and non-minority-owned restaurants that are processed by non-fintech (Panel A) and fintech (Panel B) lenders in the 2020 PPP wave for our sample. The 2020 wave spans the period from April 3, 2020 to August 8, 2020. The y-axis represents the daily dollar value of loans processed (in USD millions), and the x-axis represents 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 entry of fintech lenders on April 10, 2020 and the second vertical dashed line indicates the beginning of the second tranche of the 2020 PPP on April 27, 2020.



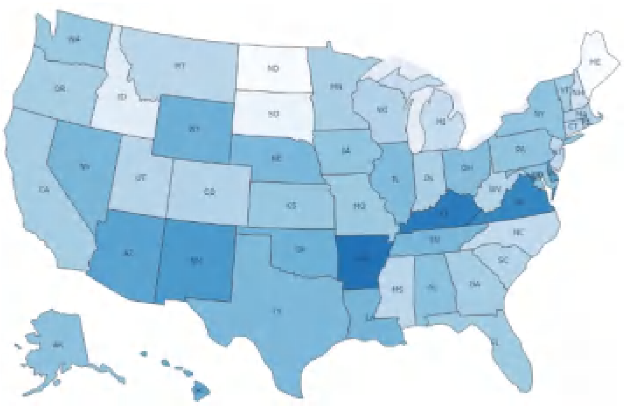
(a) 2020 PPP, Non-Fintech Lenders



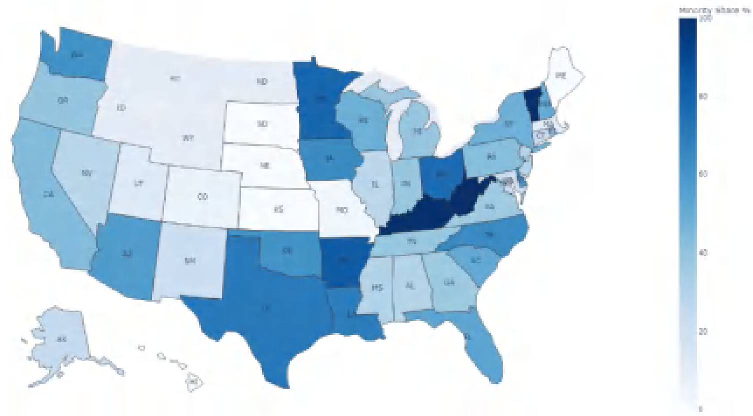
(b) 2020 PPP, Fintech Lenders

Figure 3: Percentage of Loans Distributed to Minority-owned Businesses Fintech vs. Non-Fintech (Dollar Value)

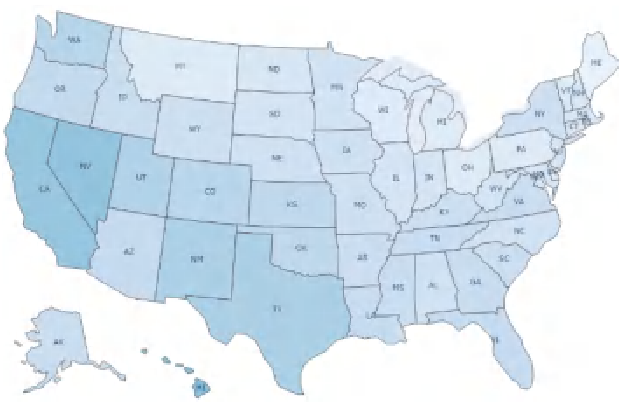
This figure plots the share of loan dollar values distributed to minority-owned businesses processed by fintech (Panels A and B) and non-fintech (Panels C and D) lenders in the 2020 and 2021 waves, based on our sample. The shares range from 0% (the lightest blue) to 100% (the darkest blue).



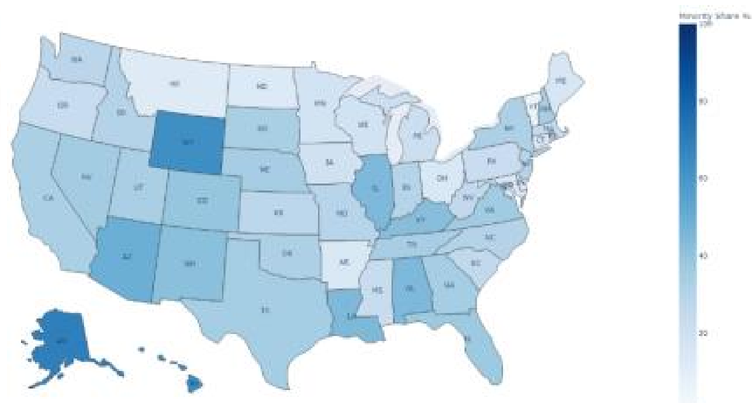
(a) Fintech in the 2020 PPP



(b) Fintech in the 2021 PPP



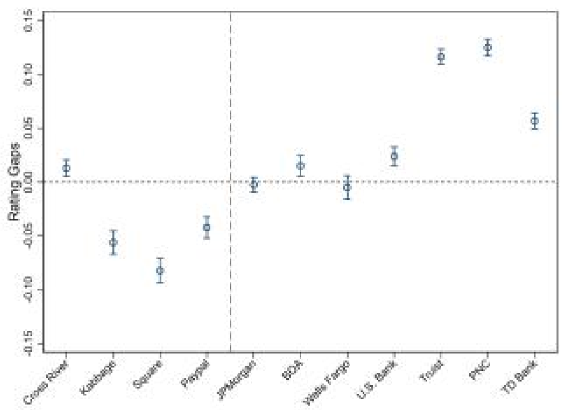
(c) Non-Fintech in the 2020 PPP



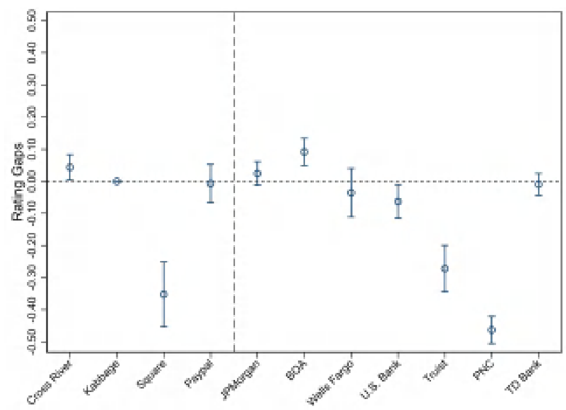
(d) Non-Fintech in the 2021 PPP

Figure 4: Minority-Non-Minority Rating Gap Fintech vs. Non-Fintech

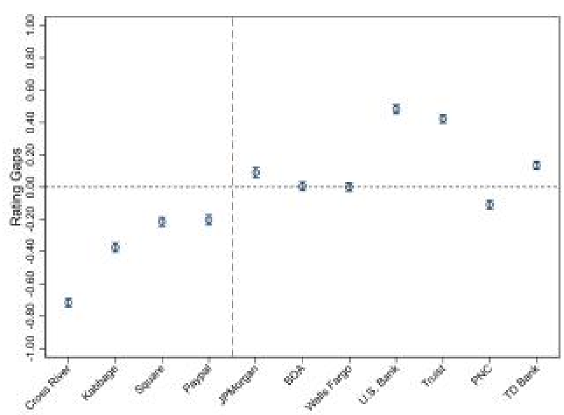
This figure plots the minority-non-minority rating gap using ratings from April 2020 to March 2021 (during the Covid crisis). The racial group and PPP wave are indicated in the captions of each figure. The y-axis represents the regression coefficients before the interaction terms between the racial group indicator and lender indicators from the regressions as in Table 7, except that I decompose the fintech indicator into several indicators for each big fintech lender and bank. 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 lenders that are not plotted. The x-axis represents each lender. I plot the biggest four fintech lenders in our sample: Cross River Bank, Kabbage, Square, and Paypal, and the largest seven banks in my sample: JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. The dependent variable, independent and control variables are the same as in Table 7. Detailed variable definitions are in Appendix Table B1. Standard errors are clustered at the restaurant-lender level.



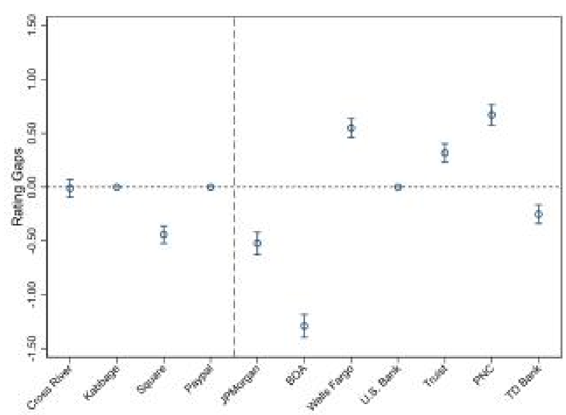
(a) 2020 PPP (Asians)



(b) 2021 PPP (Asians)

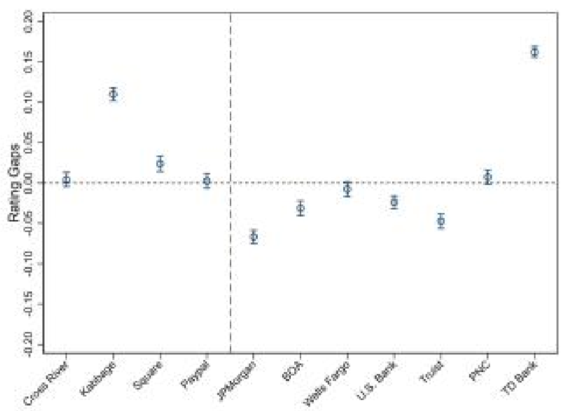


(c) 2020 PPP (African-Americans)

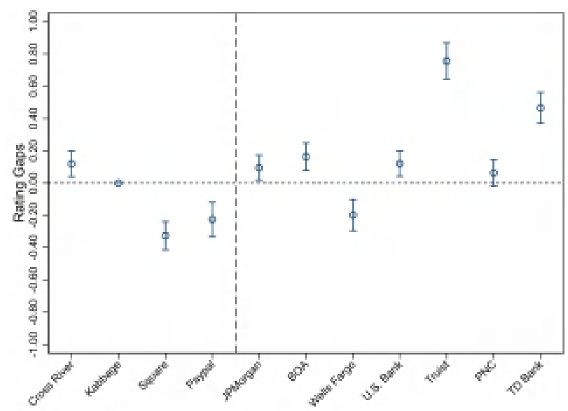


(d) 2021 PPP (African-Americans)

Figure 4: Minority-Non-Minority Rating Gap Fintech vs. Non-Fintech (Cont.)



(e) 2020 PPP (Hispanics)



(f) 2021 PPP (Hispanics)

Tables

Table 1: Summary Statistics

This table presents the summary statistics for the sample of restaurant PPP recipients merged with a meaningful Yelp link. For resturant and Detailed variable definitions are in Appendix Table B1.

Panel A: Restaurant-Level Cross Section 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	86097	0.33	0.47	0	0	0	1	1
I(African American)	92557	0.01	0.08	0	0	0	0	1	86,097	0.01	0.08	0	0	0	0	1
I(Asian)	92,557	0.18	0.39	0	0	0	0	1	86,097	0.2	0.4	0	0	0	0	1
I(Hispanic)	92,557	0.13	0.33	0	0	0	0	1	86,097	0.13	0.34	0	0	0	0	1
Employment	92,557	18.62	31.02	1	5	11	21	500	86,097	14.79	17.44	1	5	10	19	500
I(Franchise)	92,557	0.12	0.33	0	0	0	0	1	86,097	0.11	0.32	0	0	0	0	1
I(Fintech)	92,557	0.09	0.29	0	0	0	0	1	86,097	0.1	0.29	0	0	0	0	1
Δ(Date)	92,557	26.87	24.19	0	10	25	28	127	86,097	27.64	24.43	0	11	25	28	127
I(Relationships)	92,557	0.03	0.18	0	0	0	0	1	86,097	0.03	0.18	0	0	0	0	1
Rel. (N. Loans)	925,57	0.04	0.25	0	0	0	0	8	86,097	0.04	0.25	0	0	0	0	8
Rel. (A. Loan)	92,557	18	3,074	0	0	0	0	680,000	86,097	20	3,187	0	0	0	0	680,000
I(New Bank)	82,287	0.04	0.2	0	0	0	0	1	76,082	0.04	0.2	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

Panel B: Restaurant-Level Cross Section 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 American)	6,268	0.01	0.11	0	0	0	0	1	6,024	0.01	0.12	0	0	0	0	1
I(Asian)	6,268	0.22	0.41	0	0	0	0	1	6,024	0.22	0.42	0	0	0	0	1
I(Hispanic)	6,268	0.15	0.36	0	0	0	0	1	6,024	0.16	0.36	0	0	0	0	1
Employment	6,268	9.39	13.41	1	3	6	11	342	6,024	8.41	8.66	1	3	6	10	93
I(Franchise)	6,268	0.06	0.23	0	0	0	0	1	6,024	0.06	0.23	0	0	0	0	1
I(Fintech)	6,268	0.17	0.38	0	0	0	0	1	6,024	0.18	0.38	0	0	0	0	1
Δ(Date)	6,268	41.12	21.14	0	23	39	60	78	6,024	41.01	21.05	0	23	39	60	78
I(Relationships)	6,268	0.02	0.13	0	0	0	0	1	6,024	0.02	0.13	0	0	0	0	1
Rel. (N. Loans)	6,268	0.02	0.16	0	0	0	0	3	6,024	0.02	0.15	0	0	0	0	3
Rel. (A. Loan)	6,268	0	0.06	0	0	0	0	3	6,024	0	0.06	0	0	0	0	3
I(New Bank)	4,866	0.04	0.2	0	0	0	0	1	4,648	0.04	0.2	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

Panel C: Restaurant Ratings – Restaurant-Month-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
								2020 PPP First Draw								
Rating Stars	464,639	3.92	1.29	1	3	4	5	5	432,598	3.93	1.29	1	3	4	5	5
								2021 PPP First Draw								
Rating Stars	26,492	4.06	1.25	1	4	5	5	5	25,476	4.06	1.25	1	4	5	5	5

Table 2: Fintech Lenders and Minority-owned Businesses – Baseline

This table reports the linear probability regression results where the dependent variable is the Fintech loan indicator (0/1). The sample is the linked restaurant-level cross-sectional dataset. The key independent variables are African American, Asian, and Hispanic indicators which are defined as 1 for restaurants with the corresponding ethnic cuisine category. The results of the 2020 and 2021 PPP waves are presented in columns (1) - (4) and columns (5) - (8), referring to PPP loans issued during April 2020 and December 2020 and during January 2021 and March 2021, respectively. The full and matched sample are indicated through sub-column heads where the matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, business type (aggregated), food price range, and having an employment size with a difference of up to five employees. In addition to the variables reported in the table, we also control for business type fixed effects. Detailed variable definitions are in Appendix Table B1. For demonstration purposes, the dependent variable is multiplied by 100. Standard errors are clustered at the city level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	FinTech Indicator × 100							
	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African American)	9.17***	7.98***	9.06***	7.55***	20.92***	15.99***	20.95***	15.87***
	(1.63)	(1.59)	(1.65)	(1.64)	(5.16)	(5.03)	(5.15)	(5.05)
I(Asian)	8.44***	7.40***	8.15***	6.93***	11.54***	9.76***	11.20***	9.20***
	(0.41)	(0.39)	(0.41)	(0.39)	(1.39)	(1.34)	(1.40)	(1.36)
I(Hispanic)	1.22***	0.87***	0.87***	0.78**	5.67***	4.83***	5.50***	4.92***
	(0.33)	(0.32)	(0.33)	(0.32)	(1.44)	(1.43)	(1.47)	(1.45)
Employment		-0.07***		-0.15***		-0.16***		-0.30***
		(0.00)		(0.01)		(0.03)		(0.06)
I(Franchise)		-0.26		0.18		-2.64		-2.16
		(0.32)		(0.36)		(1.79)		(1.89)
N. Reviews (per 100)		0.13		0.52***		1.89**		2.07**
		(0.11)		(0.13)		(0.83)		(0.96)
Business Type FEs		X		X		X		X
Observations	92,557	92,556	86,097	86,095	6,268	6,266	6,024	6,022
Adjusted R^2	0.013	0.041	0.012	0.042	0.018	0.062	0.017	0.062

Table 3: Fintech Lenders and Minority-owned Businesses – Lending Relationships

This table reports the linear probability regression results where the dependent variable is the Fintech loan indicator (0/1). The sample is the linked restaurant-level cross-sectional dataset. In addition to the racial minority dummy variables in Table 2, regressions in this table include a dummy variable I(Relationships) that equals 1 if the borrower had SBA 7(a) or 504 loans during 2009-2019. The 2020 and 2021 PPP waves and the full and matched sample are indicated through sub-column heads where the matched sample is constructed in the same way described in Table 2. In addition to the variables reported in the table, we also control for business type fixed effects. Detailed variable definitions are in Appendix Table B1. For demonstration purposes, the fintech and lending relationship indicators are multiplied by 100. Standard errors are clustered at the city level as reported in the parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Dep. Var.	FinTech Indicator × 100			
	2020 PPP		2021 PPP	
	Full Sample (1)	Matched Sample (2)	Full Sample (3)	Matched Sample (4)
I(African American)	7.92***	7.50***	16.10***	15.98***
	(1.60)	(1.64)	(5.02)	(5.03)
I(Asian)	7.35***	6.88***	9.70***	9.14***
	(0.39)	(0.39)	(1.34)	(1.35)
I(Hispanic)	0.81**	0.72**	4.73***	4.80***
	(0.32)	(0.32)	(1.43)	(1.45)
I(Relationships) × 100	-5.52***	-5.62***	-14.74***	-15.07***
	(0.44)	(0.48)	(0.91)	(0.86)
Employment	-0.07***	-0.15***	-0.16***	-0.29***
	(0.00)	(0.01)	(0.04)	(0.06)
I(Franchise)	-0.04	0.40	-2.43	-1.95
	(0.32)	(0.36)	(1.79)	(1.89)
N. Reviews (per 100)	0.16	0.54***	1.85**	2.04**
	(0.11)	(0.13)	(0.83)	(0.95)
Business Type FEs	X	X	X	X
Observations	92,556	86,095	6,266	6,022
Adjusted R^2	0.042	0.044	0.064	0.064

Table 4: Fintech Lenders and Minority-owned Businesses – Number of Branches

This table reports the linear probability regression results where the dependent variable is the Fintech loan indicator (0/1). The sample is the linked restaurant-level cross-sectional dataset. In addition to the racial minority dummy variables in Table 2 and lending relationship dummy in Table 3, regressions in this table include *N. Branches* which is the number of bank branches in the zip code region of the restaurant that are active in 2020 based on information from FFIEC. The 2020 and 2021 PPP waves and the full and matched sample are indicated through sub-column heads where the matched sample is constructed in the same way described in Table 2. In addition to the variables reported in the table, we also control for business type fixed effects. Detailed variable definitions are in Appendix Table B1. For demonstration purposes, the fintech and lending relationship indicators are multiplied by 100. Standard errors are clustered at the city level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	FinTech Indicator × 100			
	2020 PPP		2021 PPP	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
I(African American)	7.93***	7.52***	16.13***	16.01***
	(1.59)	(1.64)	(5.02)	(5.04)
I(Asian)	7.31***	6.83***	9.60***	9.03***
	(0.39)	(0.38)	(1.34)	(1.35)
I(Hispanic)	0.81**	0.71**	4.70***	4.79***
	(0.32)	(0.32)	(1.42)	(1.45)
N. Branches	0.02	0.03	0.05	0.05
	(0.02)	(0.03)	(0.08)	(0.09)
I(Relationships) × 100	-0.06***	-0.06***	-0.15***	-0.15***
	(0.00)	(0.00)	(0.01)	(0.01)
Employment	-0.07***	-0.15***	-0.16***	-0.29***
	(0.00)	(0.01)	(0.03)	(0.06)
I(Franchise)	-0.06	0.37	-2.54	-2.06
	(0.32)	(0.36)	(1.81)	(1.91)
N. Reviews (per 100)	0.15	0.53***	1.81**	2.00**
	(0.11)	(0.13)	(0.83)	(0.96)
Business Type FEs	X	X	X	X
Observations	92,556	86,095	6,266	6,022
Adjusted R^2	0.042	0.044	0.064	0.064

Table 5: Fintech Lenders and Minority-owned Businesses – City Location

This table reports the linear probability regression results where the dependent variable is the Fintech loan indicator (0/1). The sample is the linked restaurant-level cross-sectional dataset. In addition to the independent variables in Table 2 - Table 4, regressions in this table include city fixed effects. The results of the 2020 and 2021 PPP waves are indicated through sub-column heads, referring to PPP loans issued during April 2020 and December 2020 and during January 2021 and March 2021, respectively. The full sample and matched sample are indicated through sub-column heads where the matched sample is constructed in the same way described in Table 2. In addition to the variables reported in the table, we also control for business type fixed effects. Detailed variable definitions are in Appendix Table B1. For demonstration purposes, the fintech and lending relationship indicators are multiplied by 100. Standard errors are clustered at the city level as reported in the parentheses. * p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

Dep. Var.	FinTech Indicator × 100			
	2020 PPP		2021 PPP	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
I(African American)	4.92***	4.80***	5.64	6.75
	(1.68)	(1.72)	(6.07)	(5.99)
I(Asian)	6.09***	5.84***	6.12***	5.66***
	(0.41)	(0.41)	(1.80)	(1.82)
I(Hispanic)	0.01	-0.02	3.29*	3.70*
	(0.32)	(0.33)	(1.94)	(1.98)
Employment	-0.06***	-0.13***	-0.13**	-0.30***
	(0.00)	(0.01)	(0.05)	(0.08)
I(Franchise)	-0.23	-0.06	-7.44***	-6.61**
	(0.33)	(0.37)	(2.83)	(2.93)
N. Reviews (per 100)	-0.57***	-0.28**	0.32	0.39
	(0.12)	(0.14)	(1.06)	(1.12)
N. Branches	-0.04	-0.03	-0.07	-0.05
	(0.03)	(0.03)	(0.17)	(0.17)
I(Relationships) × 100	-0.05***	-0.05***	-0.11***	-0.10***
	(0.00)	(0.01)	(0.02)	(0.02)
City FEs	X	X	X	X
Business Type FEs	X	X	X	X
Observations	88,873	82,426	4,150	3,984
Adjusted R^2	0.063	0.063	0.079	0.085

Table 6: How much do control variables explain racial disparities in fintech usage?

This table summarizes how the coefficients before the racial dummies change after controlling for different variables, based on results using the matched sample from Table 2 - Table 5. Panel A reports results from the 2020 PPP and Panel B reports results from the 2021 PPP, referring to PPP loans issued during April 2020 and December 2020 and during January 2021 and March 2021, respectively. The matched sample is constructed in the same way described in Table 2. Detailed variable definitions are in Appendix Table B1.

	Business Characteristics	Lending Relationships	N. Branches	City FE	Unexplained
Panel A: 2020 PPP					
I(African Ame.)	16.67%	0.55%	-0.22%	30.02%	69.98%
I(Asian)	14.97%	0.61%	0.61%	12.15%	87.85%
I(Hispanic)	10.34%	6.90%	1.15%	83.91%	16.09%
Panel B: 2021 PPP					
	Business Characteristics	Lending Relationships	N. Branches	City FE	Unexplained
I(African Ame.)	24.25%	-0.53%	-0.14%	44.20%	55.80%
I(Asian)	17.86%	0.54%	0.98%	30.09%	69.91%
I(Hispanic)	10.55%	1.82%	0.18%	19.82%	80.18%

Table 7: Becker's Taste-Based Discrimination, Rating Gap

This table reports the regression results from examining the difference in ratings between minority and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. The sample is the linked restaurant-month-level panel. The dependent variable is *Rating Stars*, which is calculated as the monthly average of the customer ratings from Yelp.com between April 2020 and March 2021 (during the Covid crisis), ranging from 0 to 5. Key independent variables include African American, Asian, and Hispanic indicators that are defined as 1 for restaurants with the corresponding ethnic cuisine category and the Fintech indicator that is defined as 1 for loans backed by fintech lenders. The 2020 and 2021 PPP waves and the matched and full samples are indicated through sub-column heads. The matched sample is constructed in the same way as in Table 2. 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 delivery, takeout, reservations, and outdoor seating. Detailed variable definitions are in Appendix Table B1. N. Reviews is divided by 100 for demonstration purposes. Standard errors are clustered at the restaurant level and reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(FinTech) × I(African American)	-0.23**	-0.22**	-0.22**	-0.22**	-0.19	-0.36*	-0.19	-0.37*
	(0.11)	(0.11)	(0.11)	(0.11)	(0.18)	(0.20)	(0.18)	(0.20)
I(FinTech) × I(Asian)	-0.05***	-0.05**	-0.05**	-0.05**	-0.03	-0.01	-0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)	(0.10)	(0.07)	(0.10)
I(FinTech) × I(Hispanic)	-0.02	-0.01	-0.02	-0.01	-0.18**	-0.27**	-0.18**	-0.26*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.09)	(0.13)	(0.09)	(0.13)
I(FinTech)	0.06***	0.06***	0.05***	0.06***	-0.05	0.00	-0.06	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(African American)	0.06	0.08*	0.04	0.06	-0.02	0.04	-0.02	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.11)	(0.14)	(0.11)	(0.14)
I(Asian)	-0.03***	-0.01	-0.04***	-0.02**	-0.01	0.02	-0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.11***	-0.10***	-0.11***	-0.10***	-0.15***	-0.08	-0.15***	-0.08
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
N. Reviews (per 100)	0.06***	0.06***	0.07***	0.07***	0.05***	0.04**	0.07***	0.05**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)
I(Franchise)	-1.05***	-1.00***	-1.04***	-0.98***	-0.94***	-0.83***	-0.92***	-0.79***
	(0.01)	(0.01)	(0.01)	(0.02)	(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	464,639	434,948	432,598	403,363	26,491	14,723	25,476	14,095
Adjusted R^2	0.055	0.075	0.052	0.072	0.040	0.048	0.040	0.045

Table 8: Approval Date

This table reports the regression results from examining the difference in PPP loan approval dates between minority and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. The sample is the linked restaurant-level cross-sectional dataset. The dependent variable, Δ(Approval Date-PPP Starting Date), is the difference between the PPP loan approval date and PPP starting date. The starting date is April 09, 2020, for the 2020 wave and Jan 12, 2021, for the 2021 wave. The 2020 and 2021 PPP waves are indicated in column heads. The matched and full samples are indicated through sub-column heads. African American, Asian, and Hispanic indicators are defined as 1 for restaurants with the corresponding ethnic cuisine category. The Fintech indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample is the same as in Table 2. Detailed variable definitions are in Appendix Table B1. Standard errors are clustered at the city level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Δ(Approval Date, PPP Starting Date)							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African American) × I(Fintech)	-2.00	-1.49	-2.00	-1.40	-3.61	-0.01	-3.82	-0.04
	(3.15)	(3.29)	(3.14)	(3.29)	(4.13)	(4.65)	(4.14)	(4.69)
I(Asian) × I(Fintech)	3.45***	3.68***	3.63***	3.88***	-8.11***	-7.34***	-8.20***	-7.54***
	(0.73)	(0.76)	(0.74)	(0.77)	(1.57)	-(2.16)	(1.58)	(2.17)
I(Hispanic) × I(Fintech)	1.41	0.55	1.43	0.61	-8.72***	-6.71**	-8.75***	-6.83**
	(1.12)	(1.16)	(1.12)	(1.16)	(2.04)	(2.64)	(2.06)	(2.68)
I(Fintech)	12.10***	10.72***	11.61***	10.20***	2.42**	0.66	2.38**	0.5
	(0.46)	(0.5)	(0.47)	(0.51)	(0.94)	(1.28)	(0.96)	(1.3)
I(African American)	7.63***	6.30***	7.12***	5.75***	8.71***	4.35	8.91***	4.56
	(1.26)	(1.31)	(1.27)	(1.33)	(2.65)	(2.98)	(2.72)	(3.06)
I(Asian)	8.60***	7.88***	8.12***	7.42***	2.43***	1.42	2.29***	1.28
	(0.3)	(0.32)	(0.3)	(0.32)	(0.77)	(1.09)	(0.78)	(1.1)
I(Hispanic)	4.56***	4.33***	4.44***	4.22***	3.15***	2.51*	3.18***	2.50*
	(0.28)	(0.3)	(0.29)	(0.3)	(0.89)	(1.3)	(0.9)	(1.33)
Employment	-0.08***	-0.08***	-0.18***	-0.18***	-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)	-7.22***	-7.24***	-7.02***	-7.15***	1.21	0.92	1.62	1.84
	(0.23)	(0.25)	(0.25)	(0.27)	(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	81,687	78,026	76,850	73,244	6,266	4,150	6,022	3,984
Adjusted R^2	0.114	0.135	0.117	0.137	0.03	0.036	0.019	0.025

Table 9: Structural Estimation of the Matching Game Model

This table reports estimates from the Fox (2018) matching model. All borrower and lender-specific characteristics are demeaned. *Fintech* is an indicator equal to one if the lender is a fintech lender. *Minority* is an indicator equal to one if the restaurant is owned by minority racial groups. *Lending Relationships* is an indicator equal to one if the restaurant borrowed from the lender in SBA programs during 2009-2019. *Geo Distance* is the distance in miles between the zip codes of the borrower and the lender's headquarters. *N. Branches* is the number of active bank branches of the lender in the borrower's zip code region, using bank branch information from FFIEC. The bounds of the optimization procedure are fixed at 4000 to provide scale for the coefficients. *% of Inequalities Satisfied* is the fraction of matches deemed pairwise stable using the vector of parameter estimates. *N. of Inequalities In Total* are the total number of inequalities considered in the model. Point estimates are the estimated parameters using the entire sample. 90%, 95%, and 99% confidence intervals are based on subsampling, with *, **, and *** indicate the corresponding confidence interval does not include zero. Due to computational power constraints, I estimate the model state by state and the average of the 51 states in the sample are reported in this table.

		2020 PPP	2021 PPP
Parameter Estimates			
Fintech × Minority	Point Est.	1120.72***	421.97
	90% CI	[683.20,1592.89]	[-385.55, 1284.63]
	95% CI	[520.50,1719.00]	[-671.63, 1544.80]
	99% CI	[263.32,1897.10]	[-1026.62, 1873.81]
Lending Relationships	Point Est.	3368.36***	1648.33**
	90% CI	[3210.48,3514.81]	[704.43, 2052.74]
	95% CI	[3155.48,3551.83]	[275.32, 2178.54]
	99% CI	[3063.32,3600.39]	[-145.61, 2331.14]
N. Branches	Point Est.	1144.41***	1018.40**
	90% CI	[932.89,1356.18]	[464.72, 1650.52]
	95% CI	[872.34,1419.64]	[237.96, 1898.10]
	99% CI	[774.09,1548.27]	[-137.22, 2198.52]
Geo Distance	Point Est.	-30.10***	-102.39
	90% CI	[-46.20,-5.08]	[-348.13, 93.96]
	95% CI	[-56.45,-3.43]	[-440.20, 156.31]
	99% CI	[-74.17,5.91]	[-594.88, 225.12]
Fintech × Ratings	Point Est.	437.10**	-306.94
	90% CI	[139.25,768.19]	[-1142.81, 548.09]
	95% CI	[65.16, 860.61]	[-1373.39, 810.17]
	99% CI	[-87.29,1034.99]	[-1647.14, 1242.78]
Relative Importance			
$\left\lvert\frac{\text{Fintech}\times\text{Minority}}{\text{Lending Relationships}}\right\rvert$		0.33	0.26
$\left\lvert\frac{\text{Fintech}\times\text{Minority}}{\text{N. Branches}}\right\rvert$		0.98	0.41
$\left\lvert\frac{\text{Fintech}\times\text{Minority}}{\text{Geo Distance}}\right\rvert$		14.52	4.12
% of Inequalities Satisfied		67.34%	72.72%
N. of Inequalities In Total		2,142,966	7,859

Table 10: Matching Game Model Counterfactual, Fintech Usage

This table reports counterfactual estimates of the fintech usage by minority and non-minority racial groups in the PPP under alternative matching assignments. Counterfactual matching assignments are generated by altering the parameters of the matching model and reassigning borrowers to lenders in the same state. The three left columns of the panel report the counterfactual estimates. The three right columns of the panel report the percentage of changes of the variable under each counterfactual matching assignment relative to the model predictions without altering the parameters (i.e., $\frac{Counterfactual-Model}{Model}$). The columns labeled "% of Minority Use Fintech" and "% of White Use Fintech" report the fraction of minority and non-minority borrowers using fintech, respectively, under each counterfactual matching assignment. The columns labeled "Δ" reports the difference between the minority and non-minority groups in each case. When the matching values tie, I use a random match between borrowers and lenders. To wash out the effect due to randomness in the tie-value cases, I run each counterfactual case 100 times and report the average in this table. Due to computational power constraints, I estimate the model state by state and the average of the 51 states in the sample are reported in this table.

	2020 PPP					
	Estimated Results			Compared to Model Prediction		
	% of Minority Use Fintech	% of White Use Fintech	Δ	% of Minority Use Fintech	% of White Use Fintech	Δ
Model Prediction	19.03%	2.62%	16.42%			
Random Sample	7.80%	7.03%	0.77%	-59.02%	168.78%	-95.32%
Shut Off $\beta_{\text{Fintech}\times\text{Minority}}$	5.82%	8.22%	-2.40%	-69.41%	214.15%	-114.61%
Reverse $\beta_{\text{Fintech}\times\text{Minority}}$	2.31%	9.84%	-7.53%	-87.86%	276.01%	-145.85%
Shut Off $\beta_{\text{Lending Relationships}}$	19.38%	2.45%	16.93%	1.81%	-6.33%	3.11%
Shut Off $\beta_{\text{N. Branches}}$	19.07%	2.48%	16.59%	0.22%	-5.09%	1.07%
Shut Off $\beta_{\text{Geo Distance}}$	19.00%	2.52%	16.48%	-0.16%	-3.61%	0.39%
Shut Off $\beta_{\text{Fintech}\times\text{Ratings}}$	20.21%	1.99%	18.22%	6.20%	-23.91%	11.00%
	2021 PPP					
	Estimated Results			Compared to Model Prediction		
	% of Minority Use Fintech	% of White Use Fintech	Δ	% of Minority Use Fintech	% of White Use Fintech	Δ
Model Prediction	18.71%	10.81%	7.89%			
Random Sample	14.96%	12.84%	2.12%	-20.05%	18.72%	-73.14%
Shut Off $\beta_{\text{Fintech}\times\text{Minority}}$	13.59%	14.48%	-0.89%	-27.35%	33.90%	-111.24%
Reverse $\beta_{\text{Fintech}\times\text{Minority}}$	13.12%	15.64%	-2.52%	-29.86%	44.68%	-131.96%
Shut Off $\beta_{\text{Lending Relationships}}$	18.69%	10.88%	7.80%	-0.10%	0.66%	-1.16%
Shut Off $\beta_{\text{N. Branches}}$	20.19%	10.10%	10.09%	7.95%	-6.59%	27.87%
Shut Off $\beta_{\text{Geo Distance}}$	18.76%	10.91%	7.86%	0.30%	0.87%	-0.48%
Shut Off $\beta_{\text{Fintech}\times\text{Ratings}}$	22.07%	8.95%	13.12%	17.99%	-17.25%	66.26%

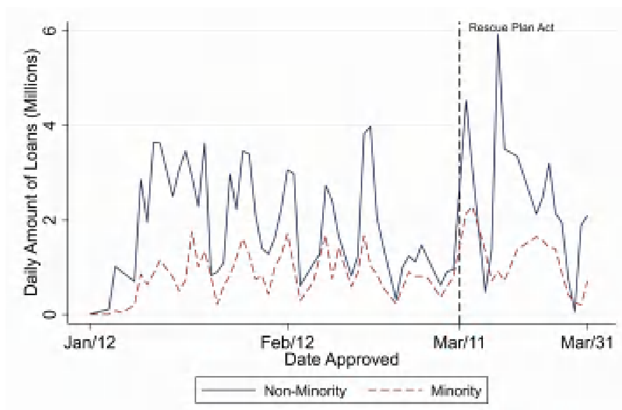
Internet Appendices

Internet Appendix A: Additional Figures

Figure A1: Minority- and Non-Minority-owned Businesses in the 2021 PPP Fintech vs. Non-Fintech

This figure plots the daily dollar value of PPP loans received by minority- and non-minority-owned restaurants processed by non-fintech (Panel A) and fintech (Panel B) lenders in the 2021 PPP wave for our sample. The 2021 wave spans from January 12, 2021, to March 31, 2021. The y-axis represents the daily dollar value of loans processed (in USD millions), and the x-axis represents 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 implementation of the American Rescue Plan Act of 2021 on March 11, 2021.

Panel A: 2021 PPP, Non-Fintech Lenders



Panel B: 2021 PPP, Fintech Lenders

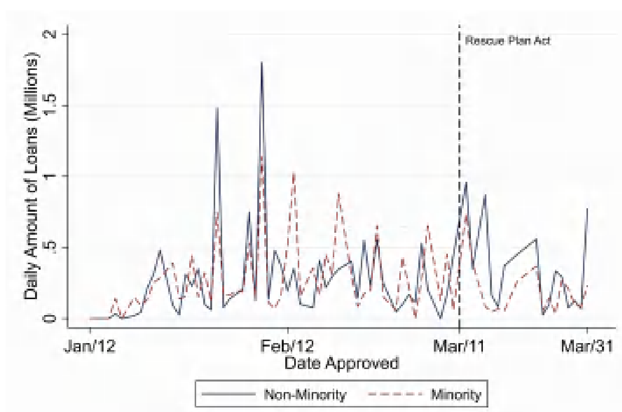
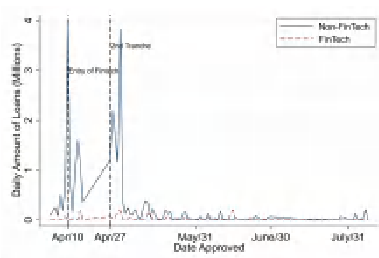


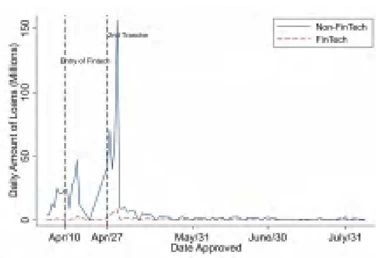
Figure A2: Loans Distributed by Fintech and Non-Fintech Lenders Across Racial Groups (Dollar Value)

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 wave for our sample. The 2020 wave spans from April 3, 2020, to August 8, 2020. Panels E to G are similar plots except they represent 2021 PPP from January 12, 2021, to March 31, 2021. The y-axis represents the daily amount of loans processed, and the x-axis represents the loan approval date. The blue solid line plots non-minority-owned restaurants and the red dashed line plots minority-owned restaurants. 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 implementation of the American Rescue Plan Act on March 11, 2021.

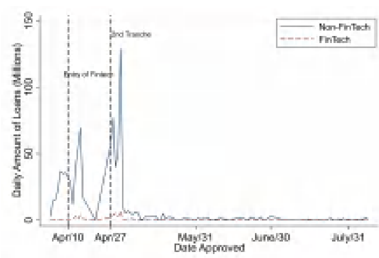
(A): 2020 PPP, African Ame.



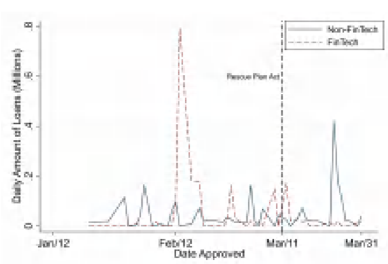
(B): 2020 PPP, Asian



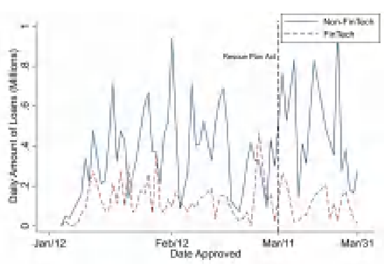
(C): 2020 PPP, Hispanic



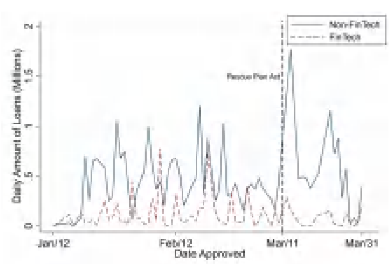
(D): 2021 PPP, African Ame.



(E): 2021 PPP, Asian



(F): 2021 PPP, Hispanic



Internet Appendix B: Additional Tables

Table B1: 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 Borrower)	1 if the restaurant is of minority food type, 0 otherwise	yelp.com
I(African American)	1 if the restaurant is of African American food type, 0 otherwise	Food type classification list
I(Asian)	1 if the restaurant is of Asian food type (including Pacific Islander), 0 otherwise	
I(Hispanic)	1 if the restaurant is of Hispanic food type, 0 otherwise *When multiple food categories, African American ≥ Asian ≥ Hispanic*	
Rating Stars	Mean of all the customer ratings in the month which range from 0 to 5	Yelp.com
Eating Policy	Dummies for the following restaurant amenities: delivery, takeout, reservations, and outdoor seating	
Food Price	Dummies for $,$$,$$$,$$$$	
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)	

Table B1: Variable Definition (Continued)

Variable Name	Definition	Data Source
Business Type FEs	Dummies based Business yype in the SBA original dataset, including 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	
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.	PPP loan-level dataset, HUD User
	We do not directly use the city information in the PPP data due to quality concerns.	
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 checks 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	1 if the lender is not federally insured, 0 otherwise	FFEIC
S&L	1 if the lender is a Savings and Loan Association, 0 otherwise	Missing if not matched with FFEIC
CU	1 if the lender is a Credit Union, 0 otherwise	
I(Relationships)	1 if the borrower previously borrowed a SBA 7(a) or 504 loan	SBA 7(a) and 504 loan-level dataset (2009-2019)
Rel. (A. Loan)	Total dollar value of SBA 7(a) and 504 loans the borrower has (million USD)	
N. Branches	The number of bank branches in the zip code region of the restaurant that are active in 2020 based on information from FFIEC.	

Table B2: The List of Fintech Lenders in the First Draw of the PPP Program

Loan Source shown in the PPP loan-level dataset includes 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.

Pair Num	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[1]	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

Table B3: Compare the Racial Group Measures PPP vs Yelp.com

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				
PPP	White	Non-White	Hispanic	African Ame.	Asian
White	74.90%	12.20%	26.90%	12.00%	4.70%
Non-White	25.10%	87.80%	73.10%	88.00%	95.30%
Hispanic	3.90%	18.30%	51.90%	1.80%	1.80%
African Ame.	4.00%	5.20%	7.50%	80.10%	0.50%
Asian	13.70%	59.50%	5.90%	1.80%	89.60%
Native Ame.	3.50%	4.80%	7.80%	4.20%	3.40%
Observations	13,327	5,498	1,806	166	3,526

Panel B: Cross Shares – Compare PPP with Yelp

	PPP					
Yelp	White	Non-White	Hispanic	African Ame.	Asian	Native Ame.
White	93.70%	40.90%	34.20%	65.00%	35.80%	63.60%
Non-White	6.30%	59.10%	65.80%	35.00%	64.20%	36.40%
Hispanic	4.60%	16.20%	61.50%	16.40%	2.10%	19.30%
African American	0.20%	1.80%	0.20%	16.20%	0.10%	1.00%
Asian	1.60%	41.10%	4.10%	2.30%	62.00%	16.20%
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 American PPP		0.35*** (0.00)		
Asian PPP			0.52*** (0.00)	
Hispanic PPP				0.68*** (0.00)
Observations	18,825			

Table B4: Compare My Sample with the Sample in Erel and Liebersohn (2020)

The difference between my sample and the EL Sample can be attributed to 1) I exclude borrowers from Puerto Rico and non-profit organizations; 2) I 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, I 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 modifications 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 B5: Lending Relationships and Fintech Usage (Dummy Variable)

This table reports the regression results from examining the difference in previous lending relationships between minority and non-minority-owned restaurants. The sample is the linked restaurant-level cross-sectional dataset. Panels A and B report the regression results where the dependent variable is I(Relationships), a dummy variable that equals 1 if the borrower had SBA 7(a) or 504 loans during 2009-2019, on the 2020 and 2021 PPP waves respectively. The 2020 and 2021 PPP waves refer to April 2020 to December 2020 and January 2021 to March 2021. African American, Asian, and Hispanic indicators are defined as 1 for restaurants with the corresponding ethnic cuisine category. The matched and full samples are indicated through sub-column heads. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table B1. For demonstration purposes, dependent variables are multiplied by 100. Standard errors are clustered at the city level as reported in the parentheses. * p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

Panel A: 2020 PPP

Dep. Var.	I(Relationships) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African American)	-1.56**	-1.48**	-0.92	-1.02	-1.49**	-1.30*	-0.76	-0.87
	(0.66)	(0.66)	(0.66)	(0.68)	(0.67)	(0.67)	(0.66)	(0.68)
I(Asian)	-1.57***	-1.50***	-0.78***	-1.04***	-1.58***	-1.45***	-0.72***	-1.00***
	(0.16)	(0.16)	(0.16)	(0.18)	(0.17)	(0.16)	(0.16)	(0.18)
I(Hispanic)	-1.64***	-1.63***	-1.05***	-0.98***	-1.68***	-1.70***	-1.11***	-1.03***
	(0.15)	(0.15)	(0.15)	(0.17)	(0.15)	(0.15)	(0.15)	(0.17)
Employment		0.98***	0.63***	0.52**		3.18***	2.34***	2.11***
		(0.2)	(0.2)	(0.21)		(0.44)	(0.43)	(0.45)
I(Franchise)			3.84***	3.80***			3.87***	3.83***
			(0.28)	(0.3)			(0.29)	(0.31)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	92,557	92,557	92,556	88,873	86,097	86,097	86,095	82,426
Adjusted R^2	0.002	0.002	0.011	0.008	0.002	0.003	0.011	0.008

Panel B: 2021 PPP

Dep. Var.	I(Relationships) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African American)	0.47	0.61	0.72	1.89	0.47	0.59	0.71	1.89
	(1.68)	(1.68)	(1.69)	(2.31)	(1.7)	(1.7)	(1.71)	(2.35)
I(Asian)	-0.88**	-0.74**	-0.45	-0.05	-0.90**	-0.78**	-0.47	-0.07
	(0.36)	(0.37)	(0.4)	(0.56)	(0.36)	(0.37)	(0.4)	(0.57)
I(Hispanic)	-0.85*	-0.82*	-0.65	0.05	-0.87**	-0.88**	-0.69	-0.02
	(0.43)	(0.43)	(0.44)	(0.66)	(0.44)	(0.44)	(0.45)	(0.67)
Employment		2.98	2.51	2.03		4.10**	3.4	4.95
		(2.06)	(2.05)	(1.61)		(2.06)	(2.13)	(3.34)
I(Franchise)			1.45	1.47			1.43	1.61
			(0.93)	(1.19)			(0.99)	(1.25)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	6,268	6,268	6,266	4,150	6,024	6,024	6,022	3,984
Adjusted R^2	0.001	0.002	0.005	0.013	0.001	0.001	0.005	-0.01

Table B6: Lending Relationships and Fintech Usage (Loan Dollar Value)

This table reports the regression results where the dependent variable is Rel. (A. Loan), which is measured using the value (in USD millions) of SBA 7(a) or 504 loans the restaurant borrowed during 2009-2019. A. Loan is winsorized at the 1% and 99% cuts. The 2020 and 2021 PPP waves as indicated through the Panels' heading. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table B1. Employment is divided by 100. Standard errors clustered at the city level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP

Dep. Var.	Rel. (A. Loan) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	-0.63*	-0.51	-0.20	-0.35	-0.52	-0.32	-0.04	-0.21
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.34)
I(Asian)	-0.61***	-0.49***	-0.11	-0.29***	-0.56***	-0.42***	-0.06	-0.23**
	(0.09)	(0.09)	(0.08)	(0.10)	(0.08)	(0.08)	(0.08)	(0.09)
I(Hispanic)	-0.58***	-0.55***	-0.25***	-0.32***	-0.52***	-0.54***	-0.25***	-0.30***
	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.09)
Employment		1.50***	1.35***	1.32***		3.31***	2.99***	2.96***
		(0.18)	(0.18)	(0.18)		(0.32)	(0.32)	(0.34)
I(Franchise)			2.19***	2.12***			2.10***	1.99***
			(0.17)	(0.18)			(0.17)	(0.18)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	92557	92557	92556	88873	86097	86097	86095	82426
Adjusted R2	0.001	0.003	0.010	-0.012	0.001	0.004	0.011	-0.010

Panel B: 2021 PPP

Dep. Var.	Rel. (A. Loan) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	-0.32*	-0.25	-0.24	-0.14	-0.33*	-0.24	-0.24	-0.15
	(0.19)	(0.19)	(0.20)	(0.27)	(0.20)	(0.19)	(0.20)	(0.29)
I(Asian)	-0.42***	-0.35***	-0.23**	-0.35*	-0.43***	-0.34***	-0.23**	-0.36*
	(0.11)	(0.10)	(0.10)	(0.21)	(0.11)	(0.10)	(0.10)	(0.21)
I(Hispanic)	-0.27*	-0.26	-0.20	-0.08	-0.28*	-0.29*	-0.23	-0.15
	(0.16)	(0.16)	(0.16)	(0.22)	(0.17)	(0.16)	(0.16)	(0.22)
Employment		1.60**	1.51**	1.69*		3.03***	2.94**	4.40**
		(0.72)	(0.72)	(0.99)		(1.13)	(1.16)	(2.10)
I(Franchise)			0.39	0.58			0.35	0.60
			(0.32)	(0.47)			(0.34)	(0.49)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	6268	6268	6266	4150	6024	6024	6022	3984
Adjusted R2	0.001	0.002	0.003	-0.094	0.001	0.003	0.003	-0.095

Table B7: Fintech and Lending Relationship (Loan Dollar Value)

This table reports the regression results where the dependent variable is the Fintech loan indicator (0/1). The 2020 and 2021 PPP waves as indicated through the Panels' heading. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table B1. Employment is divided by 100. Standard errors clustered at the city level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP

Dep. Var.	I(Fintech) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rel. (A. Loan)	-0.06***	-0.05***	-0.05***	-0.05***	-0.07***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Black)			7.99***	4.98***			7.64***	4.85***
			(1.59)	(1.67)			(1.64)	(1.71)
I(Asian)			7.43***	6.05***			7.08***	5.83***
			(0.38)	(0.40)			(0.38)	(0.40)
I(Hispanic)			0.87***	0.04			0.81**	0.02
			(0.32)	(0.32)			(0.32)	(0.33)
Employment		-7.16***	-6.39***	-6.43***		-15.43***	-13.97***	-13.60***
		(0.32)	(0.30)	(0.30)		(0.90)	(0.83)	(0.80)
I(Franchise)		-1.62***	-0.20	-0.13		-1.28***	0.11	-0.07
		(0.32)	(0.32)	(0.34)		(0.36)	(0.36)	(0.38)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	92557	92556	92556	88873	86097	86095	86095	82426
Adjusted R^2	0.000	0.031	0.041	0.062	0.000	0.034	0.042	0.063

Panel B: 2021 PPP

Dep. Var.	I(Fintech) × 100							
Sample	Full Sample				Matched Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rel. (A. Loan)	-0.22***	-0.17***	-0.16***	-0.13***	-0.23***	-0.17***	-0.15***	-0.10***
	(0.06)	(0.05)	(0.04)	(0.03)	(0.06)	(0.05)	(0.04)	(0.03)
I(Black)			16.14***	5.50			16.04***	6.60
			(5.05)	(6.08)			(5.07)	(6.01)
I(Asian)			10.10***	6.06***			9.56***	5.63***
			(1.33)	(1.80)			(1.34)	(1.82)
I(Hispanic)			4.92***	3.30*			5.00***	3.70*
			(1.42)	(1.93)			(1.44)	(1.98)
Employment		-17.36***	-13.37***	-12.17**		-31.41***	-25.83***	-29.16***
		(3.34)	(3.12)	(4.74)		(5.36)	(5.27)	(7.26)
I(Franchise)		-4.89***	-2.89	-7.65***		-4.37**	-2.37	-6.84**
		(1.79)	(1.78)	(2.74)		(1.89)	(1.88)	(2.85)
City FEs				X				X
Business Type FEs			X	X			X	X
Observations	6268	6266	6266	4150	6024	6022	6022	3984
Adjusted R^2	0.001	0.049	0.061	0.078	0.001	0.050	0.061	0.084

Table B8: Minority-Non-Minority Rating Gap (Extensions –Non-Fintech or Fintech)

This table reports the regression results from examining the difference in ratings between minority and non-minority-owned restaurants that borrow from non-fintech (Panel A) and fintech (Panel B) lenders, respectively. The sample is the linked restaurant-month-level panel dataset and we calculate the monthly average of the ratings. The sample period of ratings is April 2020 to March 2021 (during the Covid crisis). The dependent variable is the Rating Stars, which ranges from 0 to 5, based on customer ratings from yelp.com. Key independent variables include Black, Asian, and Hispanic indicators that are defined as 1 for restaurants with the corresponding ethnic cuisine category. The 2020 and 2021 PPP waves are indicated in column heads, referring to PPP loans issued during April 2020 and December 2020 and during January 2021 and March 2021, respectively. The matched and full samples are indicated through sub-column heads. The construction of the matched sample and control variables are the same as in Table 7. Detailed variable definitions are in Appendix Table B1. Employment is divided by 100 for demonstration purposes. Standard errors clustered at the restaurant level as reported in the parentheses. * p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

Panel A: Fintech Sample

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	-0.18*	-0.07	-0.19*	-0.07	-0.24*	-0.52*	-0.24*	-0.56*
	(0.10)	(0.11)	(0.10)	(0.11)	(0.14)	(0.30)	(0.14)	(0.29)
I(Asian)	-0.09***	-0.05*	-0.09***	-0.05**	-0.04	-0.04	-0.03	-0.03
	(0.02)	(0.03)	(0.02)	(0.03)	(0.06)	(0.13)	(0.07)	(0.13)
I(Hisp.)	-0.13***	-0.11***	-0.14***	-0.11***	-0.32***	-0.41***	-0.32***	-0.41**
	(0.03)	(0.04)	(0.03)	(0.04)	(0.08)	(0.16)	(0.08)	(0.16)
N. Reviews	0.07***	0.06***	0.07***	0.07***	0.09***	0.04	0.08***	0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)
I(Franchise)	-1.09***	-0.94***	-1.07***	-0.94***	-0.97***	-0.61*	-0.97***	-0.52
	(0.05)	(0.06)	(0.05)	(0.06)	(0.20)	(0.34)	(0.21)	(0.34)
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	43208	31725	42147	30882	4749	1589	4659	1576
Adjusted R^2	0.052	0.076	0.050	0.076	0.043	0.025	0.044	0.021

Table B8: Minority-Non-Minority Rating Gap (Extensions –Non-Fintech or Fintech) (Cont.)

Panel B: Non-Fintech Sample

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	0.06	0.08*	0.04	0.06	-0.02	0.04	-0.01	0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.11)	(0.13)	(0.11)	(0.13)
I(Asian)	-0.03***	-0.01	-0.04***	-0.02**	-0.01	0.03	-0.02	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
I(Hisp.)	-0.11***	-0.10***	-0.11***	-0.10***	-0.15***	-0.09	-0.15***	-0.08
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
N. Reviews	0.06***	0.06***	0.07***	0.07***	0.05**	0.03	0.07**	0.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.03)	(0.03)
I(Franchise)	-1.04***	-0.99***	-1.03***	-0.98***	-0.94***	-0.83***	-0.92***	-0.77***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.07)	(0.11)	(0.08)	(0.11)
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	421431	391707	390451	361284	21742	11207	20817	10676
Adjusted R^2	0.055	0.076	0.052	0.073	0.039	0.049	0.038	0.045

Table B9: First-Time Banks

This table reports the regression results of restaurants that borrow from lenders that are banks that participate in SBA programs for the first time. In Panel A, the dependent variable is the New Bank loan indicator (0/1) which equals one if the lender is a first-time bank in SBA programs. In Panel B, the dependent variable is the Rating Stars. The 2020 and 2021 PPP waves and the matched and full samples are indicated through sub-column heads. The sample coverage, variable definitions, the construction of the matched sample, and control variables is the same as in Table 5 for Panel A, and the same as in Table 7 for Panel B (except that Fintech lenders and non-banks are excluded). Detailed variable definitions are in Appendix Table B1. Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B), as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: First-Time Banks Usage								
Dep. Var.	I(New Bank) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African American)	-0.70	0.15	-0.59	0.38	5.35	7.54	5.16	7.36
	(0.92)	(0.93)	(0.94)	(0.96)	(6.31)	(7.76)	(6.42)	(7.87)
I(Asian)	-2.19***	-1.47***	-2.15***	-1.47***	-2.55***	-1.81**	-2.53***	-1.84**
	(0.22)	(0.21)	(0.22)	(0.22)	(0.75)	(0.82)	(0.75)	(0.85)
I(Hispanic)	-0.44*	-0.16	-0.48*	-0.22	1.10	1.99	0.95	2.09
	(0.25)	(0.24)	(0.25)	(0.25)	(1.05)	(1.50)	(1.06)	(1.56)
N. Branches	-0.05***	0.00	-0.05***	0.01	0.05	0.01	0.07	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.10)	(0.06)	(0.11)
I(Relationships) × 100	-0.04***	-0.04***	-0.04***	-0.04***	-0.05***	-0.04***	-0.05***	-0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
City FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	82,285	78,589	76,080	72,390	4,865	2,950	4,647	2,815
Adjusted R^2	0.004	0.134	0.004	0.134	0.005	0.098	0.005	0.094

Panel B: Rating Gap								
Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(New Bank) × I(African American)	0.13	0.10	0.13	0.08	0.46*	0.36	0.45*	0.36
	(0.15)	(0.19)	(0.15)	(0.19)	(0.24)	(0.31)	(0.23)	(0.31)
I(New Bank) × I(Asian)	0.00	0.00	-0.00	-0.01	-0.08	0.15	-0.10	0.07
	(0.04)	(0.05)	(0.04)	(0.05)	(0.16)	(0.34)	(0.15)	(0.36)
I(New Bank) × I(Hispanic)	0.03	0.02	0.03	0.02	-0.27	-0.29	-0.30	-0.33
	(0.04)	(0.05)	(0.04)	(0.05)	(0.18)	(0.32)	(0.18)	(0.32)
I(New Bank)	-0.01	-0.00	-0.00	-0.00	0.20***	0.25*	0.22***	0.28**
	(0.02)	(0.02)	(0.02)	(0.02)	(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	411,222	381,574	380,498	351,392	20,145	10,090	19,275	9,592
Adjusted R^2	0.055	0.076	0.052	0.073	0.041	0.049	0.040	0.048

Table B10: Non-Federally Insured Lenders

This table reports the regression results of restaurants that borrow from lenders that are not federally insured. In Panel A, the dependent variable is the Uninsured loan indicator (0/1) which equals one if the lender is not federally insured. In Panel B, the dependent variable is the Rating Stars. The 2020 and 2021 PPP waves and the matched and full samples are indicated through sub-column heads. The sample coverage, variable definitions, the construction of the matched sample, and control variables is the same as in Table 5 for Panel A, and the same as in Table 7 for Panel B (except that Fintech lenders and non-banks are excluded). Detailed variable definitions are in Appendix Table B1. Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B), as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Non-Federally Insured Institution Usage

Dep. Var.	I(Uninsured) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African American)	0.99*	0.69	0.99*	0.68	-0.63***	-0.63	-0.61***	-0.66
	(0.58)	(0.56)	(0.59)	(0.57)	(0.22)	(0.54)	(0.23)	(0.56)
I(Asian)	0.28***	0.26**	0.23**	0.21*	2.24***	0.89	2.30***	0.91
	(0.10)	(0.11)	(0.10)	(0.11)	(0.57)	(0.69)	(0.58)	(0.71)
I(Hispanic)	-0.04	0.01	-0.05	0.00	-0.26	-0.65	-0.22	-0.58
	(0.08)	(0.08)	(0.08)	(0.08)	(0.31)	(0.47)	(0.32)	(0.48)
N. Branches	-0.00	-0.01	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.04)
I(Relationships) × 100	-0.00***	-0.00***	-0.00***	-0.00***	-0.01***	-0.00	-0.01***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
City FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	85,349	81,702	79,145	75,502	5,298	3,321	5,079	3,184
Adjusted R^2	0.001	0.053	0.001	0.053	0.008	0.038	0.008	0.038

Panel B: Rating Gap

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Uninsured)× I(African American)	-0.30	-0.35	-0.31	-0.39	-	-	-	-
	(0.29)	(0.28)	(0.30)	(0.28)				
I(Uninsured) × I(Asian)	-0.10	-0.08	-0.08	-0.08	-0.15	-0.22	-0.22	-0.22
	(0.09)	(0.10)	(0.09)	(0.10)	(0.21)	(0.38)	(0.20)	(0.38)
I(Uninsured) × I(Hispanic)	-0.08	-0.01	-0.08	-0.02	0.58***	0.04	0.49***	0.01
	(0.16)	(0.17)	(0.16)	(0.17)	(0.16)	(0.34)	(0.15)	(0.35)
I(Uninsured)	-0.04	-0.03	-0.04	-0.02	-0.04	0.24	0.04	0.25
	(0.06)	(0.07)	(0.06)	(0.07)	(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	427,705	398,417	396912	368,112	21,815	11,194	20,931	10,694
Adjusted R^2	0.055	0.076	0.052	0.073	0.040	0.041	0.039	0.035

Table B11: Credit Unions

This table reports the regression results of restaurants that borrow from credit unions and other lenders in the FFIEC list. The sample is the linked restaurant-level cross-sectional dataset (Panel A) and the linked restaurant-month-level panel dataset (Panel B). The sample period of ratings is April 2020 to March 2021 (during the Covid crisis). The CU loan indicator (0/1) equals one if the lender is a credit union. The 2020 and 2021 PPP waves are indicated in column heads. The matched and full samples are indicated through sub-column heads. Other variable definitions, the construction of the matched sample, and control variables for Panel A and Panel B are the same as in Table 2 and Table 7, respectively. Detailed variable definitions are in Appendix Table B1. We only include lenders that can be matched with the FFIEC lender list. Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B) and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Credit Unions Usage

Dep. Var.	I(CU) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	1.87*	2.39**	1.90*	2.50**	6.48	7.42	6.10	7.09
	(1.02)	(1.02)	(1.05)	(1.04)	(5.75)	(6.55)	(5.70)	(6.57)
I(Asian)	-1.47***	-1.50***	-1.49***	-1.57***	-2.06***	-2.68***	-2.18***	-2.79***
	(0.17)	(0.21)	(0.17)	(0.21)	(0.71)	(0.87)	(0.72)	(0.90)
I(Hispanic)	0.15	0.51**	0.21	0.53**	-0.73	0.03	-0.87	0.28
	(0.27)	(0.25)	(0.27)	(0.26)	(0.94)	(1.34)	(0.94)	(1.35)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	85349	81702	79145	75502	5298	3321	5079	3184
Adjusted R2	0.004	0.099	0.004	0.098	0.004	0.070	0.008	0.084

Panel B: Rating Gap

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black) × I(CU)	-0.13	0.03	-0.12	0.04	0.48**	0.61**	0.50**	0.70**
	(0.18)	(0.16)	(0.18)	(0.16)	(0.20)	(0.27)	(0.20)	(0.28)
I(Asian) × I(CU)	-0.13***	-0.12**	-0.12***	-0.11**	-0.01	0.12	0.00	0.17
	(0.04)	(0.05)	(0.04)	(0.05)	(0.13)	(0.23)	(0.13)	(0.24)
I(Hisp.) × I(CU)	0.01	0.01	0.00	0.01	-0.01	0.26	-0.01	0.29
	(0.04)	(0.05)	(0.04)	(0.05)	(0.14)	(0.27)	(0.15)	(0.27)
I(CU)	0.11***	0.11***	0.11***	0.11***	0.11*	-0.11	0.10	-0.18
	(0.02)	(0.02)	(0.02)	(0.02)	(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	427705	398417	396912	368112	21815	11194	20931	10694
Adjusted R2	0.052	0.073	0.049	0.069	0.041	0.042	0.038	0.037

Table B12: CDFIs/CDCs

This table reports the regression results of restaurants that borrowed from community development-oriented lenders and banks. The sample is the linked restaurant-level cross-sectional dataset (Panel A) and the linked restaurant-month-level panel dataset (Panel B). The sample period of ratings is April 2020 to March 2021 (during the Covid crisis). In Panel A, the dependent variable is the CDC loan indicator (0/1) that equals one if the lender is a CDFI or CDC. In Panel B, the dependent variable is the Rating Stars, which range from 0 to 5, based on customer ratings from yelp.com. The 2020 and 2021 PPP waves are indicated in column heads. The matched and full samples are indicated through sub-column heads. Other variable definitions, the construction of the matched sample, and control variables for Panel A and Panel B are the same as in Table 2 and Table 7, respectively. Detailed variable definitions are in Appendix Table B1. Fintech lenders and non-banks are excluded. Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B) and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: CDFIs/CDCs Usage

Dep. Var.	I(CDC) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black)	2.37***	2.27***	2.38***	2.33***	5.74	3.25	5.84	3.34
	(0.77)	(0.81)	(0.79)	(0.83)	(3.70)	(3.82)	(3.76)	(3.88)
I(Asian)	0.32***	0.15	0.29***	0.11	-0.50	-1.76**	-0.60	-2.07***
	(0.09)	(0.10)	(0.09)	(0.10)	(0.44)	(0.73)	(0.46)	(0.74)
I(Hispanic)	0.65***	0.53***	0.66***	0.55***	0.53	-0.74	0.41	-0.87
	(0.16)	(0.17)	(0.16)	(0.18)	(0.67)	(0.87)	(0.62)	(0.83)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	82819	79121	76603	72910	4961	3033	4740	2890
Adjusted R2	0.002	-0.013	0.002	-0.016	0.003	0.015	0.003	0.006

Panel B: Rating Gap

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black) × I(CDC)	0.05	-0.01	0.05	-0.01	0.23	0.22	0.26	0.23
	(0.15)	(0.17)	(0.15)	(0.17)	(0.29)	(0.36)	(0.28)	(0.35)
I(Asian) × I(CDC)	-0.07	-0.08	-0.07	-0.09	-0.30	-0.09	-0.25	-0.18
	(0.08)	(0.09)	(0.08)	(0.09)	(0.19)	(0.29)	(0.19)	(0.28)
I(Hisp.) × I(CDC)	0.06	0.11	0.05	0.11	-0.06	0.32	-0.03	0.45
	(0.09)	(0.10)	(0.09)	(0.10)	(0.19)	(0.28)	(0.20)	(0.28)
I(CDC)	0.07	0.04	0.07	0.04	0.17**	0.05	0.12	0.03
	(0.05)	(0.05)	(0.05)	(0.06)	(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	414237	384558	383485	354350	20611	10450	19715	9915
Adjusted R2	0.052	0.073	0.048	0.069	0.042	0.053	0.039	0.049

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 (Panel A) and in 2021 (Panel B) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 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	

Panel B: 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 regression results from examining the difference in PPP loan approval dates between minority and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. The sample is the linked restaurant-level cross-sectional dataset. The starting dates of the sample are indicated in column heads. The dependent variable, Δ(Approval Date-PPP Starting Date), is the difference between the PPP loan approval date and PPP starting date. The key independent variables include Black, Asian, and Hispanic indicators that are defined as 1 for restaurants with the corresponding ethnic cuisine category, the Fintech indicator that is defined to be 1 for loans backed by fintech lenders. The matched and full samples are indicated through sub-column heads. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table B1. Employment is divided by 100 for demonstration purposes. Standard errors clustered at the city level as reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Δ(Approval Date-PPP Starting Date)							
Sample	From April 3, 2020				From April 27, 2020 (Second Tranche)			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Black) × I(Fintech)	-3.30	-2.20	-3.12	-2.01	0.42	-0.68	0.39	-0.52
	(3.10)	(3.25)	(3.10)	(3.26)	(3.16)	(3.42)	(3.16)	(3.42)
I(Asian) × I(Fintech)	2.23***	3.11***	2.52***	3.39***	5.35***	4.22***	5.44***	4.38***
	(0.74)	(0.76)	(0.74)	(0.77)	(0.75)	(0.78)	(0.75)	(0.79)
I(Hispanic) × I(Fintech)	0.80	0.06	0.83	0.11	3.72***	2.87**	3.72***	2.94**
	(1.12)	(1.15)	(1.11)	(1.15)	(1.18)	(1.25)	(1.17)	(1.25)
I(Fintech)	14.31***	11.93***	13.63***	11.27***	7.75***	7.81***	7.46***	7.45***
	(0.47)	(0.52)	(0.48)	(0.52)	(0.47)	(0.51)	(0.47)	(0.51)
I(Black)	9.63***	7.61***	8.88***	6.86***	3.61***	3.03**	3.44***	2.90**
	(1.23)	(1.29)	(1.24)	(1.29)	(1.31)	(1.36)	(1.33)	(1.38)
I(Asian)	10.37***	9.08***	9.72***	8.47***	4.24***	4.39***	4.13***	4.26***
	(0.32)	(0.33)	(0.31)	(0.33)	(0.29)	(0.31)	(0.29)	(0.31)
I(Hispanic)	5.47***	4.98***	5.30***	4.84***	1.69***	1.94***	1.74***	1.94***
	(0.28)	(0.28)	(0.28)	(0.29)	(0.33)	(0.35)	(0.33)	(0.35)
Employment	-0.09***	-0.09***	-0.20***	-0.19***	-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)	-8.15***	-7.91***	-7.93***	-7.89***	-5.62***	-5.35***	-5.49***	-5.17***
	(0.20)	(0.21)	(0.22)	(0.23)	(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	92556	88873	86095	82426	56715	53348	54437	51109
Adjusted R2	0.140	0.176	0.142	0.176	0.066	0.085	0.068	0.087

Table B15: Controlling for Approval Date Fixed Effects

This table reports the regression results of restaurants that borrow from fintech lenders. I control for approval date fixed effects in addition to the controls in specifications reported in Table 5 and Table 7. In Panel A, the dependent variable is the fintech lender indicator (0/1). In Panel B, the dependent variable is the Rating Stars. The 2020 and 2021 PPP waves and the matched and full samples are indicated through sub-column heads. The sample coverage, variable definitions, the construction of the matched sample, and control variables is the same as in Table 5 for Panel A, and the same as in Table 7 for Panel B. Detailed variable definitions are in Appendix Table B1. Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B), as reported in the parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Panel A: Fintech Usage

Dep. Var.	I(Fintech) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African American)	4.09***	2.42	3.95**	2.48	16.93***	7.90	17.03***	9.31
	(1.52)	(1.58)	(1.56)	(1.62)	(4.94)	(6.00)	(4.95)	(5.87)
I(Asian)	3.18***	3.02***	2.98***	2.94***	8.90***	6.48***	8.34***	6.18***
	(0.32)	(0.34)	(0.32)	(0.35)	(1.31)	(1.79)	(1.32)	(1.82)
I(Hispanic)	-1.02***	-1.26***	-1.03***	-1.25***	4.19***	3.66*	4.39***	4.19**
	(0.29)	(0.30)	(0.30)	(0.31)	(1.42)	(1.97)	(1.44)	(2.03)
N. Branches	0.04*	-0.00	0.04**	0.00	0.02	-0.12	0.02	-0.11
	(0.02)	(0.03)	(0.02)	(0.03)	(0.08)	(0.17)	(0.09)	(0.17)
I(Relationships) × 100	-0.03***	-0.03***	-0.03***	-0.03***	-0.16***	-0.13***	-0.16***	-0.13***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
City FEs		X		X		X		X
Approval Date FEs	X	X	X	X	X	X	X	X
Other Controls	X	X	X	X	X	X	X	X
Observations	92,553	88,870	86,092	82,423	6,266	4,148	6,022	3,982
Adjusted R^2	0.104	0.114	0.104	0.114	0.095	0.095	0.095	0.102

Panel B: Rating Gap

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(FinTech) × I(African American)	-0.23**	-0.22*	-0.23**	-0.21*	-0.15	-0.35*	-0.16	-0.37*
	(0.11)	(0.11)	(0.11)	(0.11)	(0.18)	(0.21)	(0.18)	(0.21)
I(FinTech) × I(Asian)	-0.05**	-0.04*	-0.05**	-0.04*	-0.03	0.01	-0.02	0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)	(0.10)	(0.07)	(0.10)
I(FinTech) × I(Hispanic)	-0.01	0.00	-0.02	-0.00	-0.17**	-0.28**	-0.17*	-0.27**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.09)	(0.13)	(0.09)	(0.13)
I(FinTech)	0.05***	0.05***	0.05***	0.05***	-0.06	0.01	-0.06	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.06)	(0.04)	(0.07)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Approval Date FEs	X	X	X	X	X	X	X	X
Other Controls	X	X	X	X	X	X	X	X
Observations	464,638	434,947	432,597	403,362	26,491	14,721	25,476	14,093
Adjusted R^2	0.055	0.076	0.052	0.073	0.043	0.056	0.042	0.052

Internet Appendix C: Data Construction

Internet Appendix C1 Identify Fintech Lenders

The principal source of the fintech company list I use for this study is from the SBA official website as well as the local SBA websites. I start with the fintech company list published on sba.gov.[1] I manually read the PPP lender list published on the local SBA website of all states. Arizona, California, Maryland, and North Carolina include a section on non-traditional lenders in their PPP lender lists. I include those lenders in the fintech company list as well. Finally, I 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

I manually go through the entire sample of 128 non-bank lenders in the PPP loan-level dataset and do not identify any lenders that are clearly a fintech company but have not appeared in the above-described sources. Admittedly, some non-bank lenders may have collaborations with fintech companies, but I do not include those cases because banks may also cooperate with fintech companies to some degree.[2] However, it is very time-consuming and needs more direct information to identify all the partnerships between fintech companies and banks, and other lenders without adding more insights to the analysis. Therefore, I classify fintech and non-fintech lenders based on the SBA official lists and the above three lists from the news.

Since the lists published on SBA websites and other news sources are primarily aimed at helping borrowers to find a suitable platform or place to apply for the PPP loan, they show the name of the

[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 that work with fintech companies: Ally Bank, Bank of Hope, and Citizens Business Bank, etc. are shown to work with Lendistry in PPP.

lending platform instead of the lender backing the loan and therefore are not the same as the lender recorded in the PPP dataset in some cases. Therefore, for each fintech company, I manually read their website and google search-related information 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. In the table, I 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

Internet Appendix C2 Lenders Classifications and Matching with FFIEC

This appendix describes the lender classifications and how I match the PPP lenders with Federal Financial Institutions Examination Council (FFIEC) financial institutions.

1. Lender Classification

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

1.1 Non-Banks

I 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.). I use regular expressions on lender names and define the lender as a bank if either the name of the originating and the servicing lender satisfies the regular expression.[3] Examples of regular expressions contain "bank", ending with "N.A." or "National Association", and containing "Production Credit Association". For the part that does not contain expressions satisfying the regular expressions, and therefore in the list of non-banks, I 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 5,469 banks and 128 non-banks.

1.2 CDFI Loan Funds and 504 CDC

For my study, I further classify the non-banks into lenders that have higher weights on community development and other non-bank lenders. I use two sources of information. First, I match the PPP lenders with the loan funds in the official list of "List of Certified Community Development Financial Institutions (CDFIs) with Contact Information as of October 14, 2020" published on cdfifund.gov

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

using an exact name match. This gives 42 matches with the CDFI list. For the remaining 86 non-bank lenders, I manually checked them with the official CDFI list and find 24 pairs of matched lenders.

Second, I identify Certified Development Company (CDC) using the list of lenders that participated in previous 504 programs (SBA 504 programs are small business loan programs where the lender is CDC). I adjust lender names using the lender cleaning code as in the process of other steps related to lender names. I do not consider other non-banks whose names contain words like "community", and "development" as community development-related lenders if they are not in the CDFI and the CDC list.

In total, I identify 66 CDFIs and 23 CDCs, with eight entries in both categories.

1.3 Fintech Non-Banks

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

1.4 Other Non-Banks

I classify the rest 35 non-bank lenders in the category of other non-banks.

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

I then match the PPP lenders with financial institutions on the FFIEC list. The starting sample is 3,701 PPP lenders who 1) are lenders in the 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. I 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, I define a match between the FFIEC financial institutions and PPP lenders when the two lenders have the same name and are in the same city in the same state. The city and state information that I use from FFIEC is the lender's headquarters location. I search for different variants of the lender name in the matching process. For example, "XX FCU" in place of "XX Federal Credit Union". This gives a total match of 3,511 lenders.

For the remaining 190 unmatched lenders, I manually search for the lender name from FFIEC website and match it with the FFIEC lender with the same name (including the same name but different variants), a 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 43 unmatched lenders are classified as finance companies that are not included in the FFIEC lender sample. Among the 43 lenders, 6 are fintech lenders under my definition.

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

3. Further Classification for FFIEC Matched Lenders

For lenders matched with FEIEC, I classify lenders into banks vs non-banks, federally insured institutions vs non-federally insured institutions, credit unions vs non-credit unions, and savings & loan associations vs non- savings & loan associations based on lender information from FFIEC.

Bank: I use a broad definition of banks, meaning any depository institution. I 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 a 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. Their entity type is "Domestic Entity Other (DEO)" and thus I keep them as non-banks. 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 the classifications in step 3. Among the eight DEO lenders, five are farm credit institutions, and I keep them as non-banks. I adjust the rest three (First Western SBLC, Inc, Capital One, National Association, and First National Bank Texas) into the non-bank category. Among the banks identified by name, only 20 are unmatched by FFIEC. This gives additional validation to my code-based classification of banks and non-banks.

Table C2-2 summarizes the number of pairs of originating and servicing lenders in each category in my final analysis sample.

Table C2-1 Number of Lender Pairs in Each Category

Category		N. in the entire PPP sample
Banks	Fintech	42
	Non-fintech	4,131
Non-Banks	CDFI/CDC	56
	Fintech	11
	Others	30

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

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

1. Matching Steps

The starting sample is the 372,541 loans assigned to businesses 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, the 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 the name and address adjustments, I am also able to identify the first draw participants who reapplied for the second draw.

Step 1: Basic sample cleaning

The basic sample cleaning serves two purposes. First, by unifying and deleting suffixes and prefixes, the business name and address are more likely to be what appears on yelp.com, which facilitates the automatic search and code-based match steps. Second, as I 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 that participated in the PPP and PPS. I 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 is 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, I have 3,500 observations that have the same adjusted business name and 5-digit zip code. I do two rounds of manual checks on these 3,500 observations. In the first round, I detect simple cases where the addresses are either exactly the same but written in different formats (e.g., "1502 j f kennedy dr" and "1502 jfk drive") or with a very small difference in the road number (e.g., "1651 w ogden ave" and "1659 w ogden ave"). I assign the same business entity ID to the two observations. After this round of checks, I have a rest of 1,370 observations. Then, I do a second round of manual checks and google searches to gain additional information to decide whether the business name and address in the dataset are for the same restaurant. I also gain the yelp link alongside. I find the yelp links for 1,058 observations, with 529 pairs for the same restaurant where I assign the same business entity ID and 44 observations that are different restaurants.

After the above-described steps, I 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

I 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 searching on yelp.com to find the most closely related restaurants. In both searches, I 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. I use zip code instead of the city because zip code is for a much smaller region than cities in most cases. In addition, as the city information in the original PPP data has many typos, using zip code instead of the city can immune the results from the noise in the original data.

I 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, I 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, I 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, I complement the search results with an address search to have a higher matching rate. For time-saving reasons, I include the first ten search results suggested by Yelp (i.e., the search outcomes on the first page on yelp.com) for the next matching step.

One potential caveat in the search procedure is that the results suggested by Yelp might be incomplete and therefore I miss the correct match. However, as Yelp is a widely-used restaurant search engine with a good reputation, such a possibility is low and unlikely to be systematically biased. In most cases, Yelp search engine works with good precision and therefore it is very unlikely that the correct match is beyond the first ten results. Code for the search is available upon request.

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

I employ matching criteria that are rather strict: only include the pair as "matched" when I am confident that both the name and address in the two data sources have meaningful connections. I 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

I employ the same code-based adjustments of the names and addresses as described in Section 3 Name and Address Cleaning Mapping for the counterparts in yelp to have a uniform representation of the same name/address. This step is important for improving the matching precision. For franchise names, I further shorten the names from the version used for automatic search as the names on yelp.com is shorter in most cases. I 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

I use a 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, I 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 I 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

When a random check suggests precision lower than 95%, I manually check and correct all the code-suggested matches. After the steps above, I have a sample of 104,429 total matches. I also add in the 556 matches from the manual step in 1.1, so I have a sample of 104,985 matches until this step.

Step 3.5 Other adjustments

There are very few cases where one loan is matched with several yelp links. I manually check the 689 matches where the yelp link is duplicated. I pick the links 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 I pick the latter. When both links are for the same restaurant, I choose the one with more reviews or a more complete sample period before and after the Covid-19 crisis.

Until this step, I 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 the rather strict matching criteria to ensure the likelihood of false positives is very low, the matching rate is reasonable and the matched sample is useful. I 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 where I manually classify the business labels on yelp.com into labels for restaurants and non-restaurants. This gives a sample of 101,803 matches between a PPP loan and a yelp link for restaurants. I further exclude borrowers in Puerto Rico, Northern Mariana Islands, Guam, U.S. Virgin Islands and have a sample of 101,753 matches.

A final step of adjustment is to active restaurants before Covid. For the empirical analysis, I 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. My final sample has 98,825 restaurant PPP recipients.

2. Matching Criteria

This section describes the criteria based on which I 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. I pose a restriction that at least one (name or address) is exactly the same. I check 100 random samples for each case of the different combinations of name/address and exact/containing. In all cases, I have a 100% accuracy of matches for the random sample. Therefore, I consider all matches under criterion 1 are correct matches. Combining the matched search outcomes from both the name search and address search, I have 66,018 matches for non-franchise restaurants and 12,979 for franchise restaurants.

For the following criteria, I 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 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, I 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 I consider this type of mis-input to be of a much lower percentage for franchised restaurants than for non-franchised restaurants as the separation between the business, and the owner is clearer in franchised restaurants 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, I 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. I check 100 random samples and have a 98% accuracy of matches. Therefore, I consider all matches under criteria 2 are correct matches. Combining the matched search outcomes from both the name and address searches, I 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, I pose the restriction that PPP data and the yelp search outcome are in the same 5-digit zip code. I check 100 random samples and have a 100% accuracy of matches. Therefore, I consider all matches under criteria 3 are correct matches. Combining the matched search outcomes from both the name and address searches, I 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, I pose the restriction that PPP data and the yelp search outcome are in the same 5-digit zip code. I do not pose the condition that the addresses in both data sources have a containing relationship. I check 100 random samples and the accuracy is low. Therefore, I manually check all code-suggested results and adjust the match when the one suggested by code matching is incorrect. After the manual correction, I 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 being of addresses like typos or different formats, 1,283 are of addresses either or a home address or corporation office, and 513 of a wrong yelp address. I 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, I use the FranchiseName as the search input instead of using the BorrowerName in the search for non-franchised restaurants.

Early data entries of the PPP data might be incomplete and therefore I adjust the franchise name across the PPP and PPS whenever the franchise name is available for the same business entity ID. I 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, I 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. I describe below the details on the criteria I use to judge whether the franchise name is a food or drinking place.

1. If the franchise name ends with the following keywords, 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 misspelling: 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, I search the franchise name in google with the 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 chain or not.

   Common miscategorized franchise names are art studios, car dealers, elderly care services, fitness clubs, optometrists, and training programs.

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

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. I drop the observations where the franchise name is not, so I 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, I generate a name for the search step. I 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 I make code-based adjustments by deleting suffixes such as "corporation", "llc", "ltd". This serves the purpose of making 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	Jul-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 mean of key variables of PPP restaurant borrowers in the following samples: borrowers without a Yelp link, borrowers in the empirical analysis sample of this paper, and borrowers with a Yelp link but not in the empirical analysis sample. The difference between the second and the third sample lies in that some borrowers with a Yelp link are inactive (with no reviews) after 2018 and therefore not in the empirical analysis sample.

Table C3-3

This table reports the mean of key variables of PPP restaurant borrowers in the following samples: borrowers without a Yelp link, borrowers in the empirical analysis sample of this paper, and borrowers with a Yelp link but not in the empirical analysis sample. The sample includes restaurant borrowers in the PPP program in both years.

	Without Yelp Link	**Analysis Sample**	With Yelp Link But Not in Analysis Sample
Mean			
Initial Approval Amount	103382.5	78204.27	45031.88
Current Approval Amount	102817.9	77993.58	44976.03
Approved Date	6/27/2020	5/18/2020	5/26/2020
Jobs Reported	20	18	11
Share			
Franchise	7.47%	11.84%	20.35%
Corporation	29.17%	33.91%	32.27%
Limited Liability Company	35.85%	38.95%	33.51%
Partnership	2.36%	3.01%	2.99%
Subchapter S Corporation	11.58%	13.99%	15.72%
Sole Proprietorship	15.94%	9.20%	14.61%
Self Employed	3.02%	0.62%	0.57%
Others	2.08%	0.31%	0.34%
Observations	270,738	98,825	2,978

While the analysis sample has loans of smaller size and approved earlier, the difference is not small. The analysis sample is also more likely to be franchised and in a formal corporate format such as corporation and L.L.C. than sole proprietorship and self-employed. This reflects the fact that more formal businesses are more likely to have active Yelp links. Nevertheless, the difference is the share of different business types between the unlinked sample and the analysis sample is less than 3%. Overall, the analysis sample does not differ significantly from the unliked sample. On the other hand, the inactive yelp sample (the sample with a yelp link but not in the analysis sample) is much smaller compared to the unlinked sample in terms of loan size and employment size. The inactive yelp sample is also much more likely to be franchised, perhaps meaning the chains moved to other locations.

Table C3-4 shows the share of fintech loans and the total number of loans for PPP restaurant borrowers in the following samples: borrowers without a Yelp link, borrowers in the empirical analysis sample of this paper, and borrowers with a Yelp link but not in the empirical analysis sample in each business type. For the business type of Corporation, Limited Liability Company, Partnership, Subchapter S Corporation, and Self Employed, the fintech share is similar for the analysis and unlinked samples. Restaurants with the business type of Sole Proprietorship and Others have a much higher degree of fintech usage in the unlinked sample. Those are relatively smaller "restaurants" with limited types of services, for example, food trucks. Moreover, restaurants of a business type such as Sole Proprietorship and Others are less likely to have a valid and active Yelp link compared with other types of restaurants (see Table C3-3).

Table C3-4

This table reports the share of fintech loans and the total number of loans for PPP restaurant borrowers in the following samples: borrowers without a Yelp link, borrowers in the empirical analysis sample of this paper, and borrowers with a Yelp link but not in the empirical analysis sample, across different business types. The sample includes restaurant borrowers in the PPP program in both years.

	Without Yelp Link		**Analysis Sample**		With Yelp Link But Not in Analysis Sample	
Business Type	FinTech	Total N.	FinTech	Total N.	FinTech	Total N.
Corporation	9.56%	78,982	10.17%	33,515	8.64%	961
Limited Liability Company	8.52%	97,071	8.57%	38,493	5.41%	998
Partnership	7.63%	6,380	9.04%	2,976	4.49%	89
S Corporation	8.66%	31,341	9.50%	13,829	4.91%	468
Sole Proprietorship	32.89%	43,143	9.17%	9,094	3.68%	435
Self Employed	58.80%	8,178	63.34%	611	47.06%	17
Others	31.35%	5,643	8.79%	307	30.00%	10
Total		270,738		98,825		2,978

Table C3-5 compares the racial group shares based on the information in the PPP loan-level data for restaurant borrowers without a Yelp link, borrowers in the empirical analysis sample of this paper, and borrowers with a Yelp link but not in the empirical analysis sample. 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 C3-5

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. I report results for borrowers without a Yelp link, borrowers in the empirical analysis sample of this paper, and borrowers with a Yelp link but not in the empirical analysis sample separately.

	Without Yelp Link	**Analysis Sample**	With Yelp Link But Not in Analysis Sample
White	54.74%	64.71%	74.01%
Hispanic	11.54%	14.49%	9.52%
African American	21.64%	4.36%	3.36%
Asian	20.13%	26.69%	17.28%
Native American	3.14%	3.88%	4.43%
Obs.	57,255	18,826	654

Internet Appendix D: Model Discussions and Proofs

4.1 Race-Neutral Case

In the race-neutral case, $p_{i,j}(\gamma_i, \theta_{i,j}) = g(\gamma_i)$ for borrowers matched with traditional lenders. $p_{i,j}(\gamma_i, \theta_{i,j}) = g(\gamma_i) + h(\theta, \gamma_i)$ for borrowers matched with fintech lenders. I assume that $M^m + M^n > M^f + M^b$. Therefore, not all borrowing demand is satisfied in equilibrium.

The equilibrium in this setting is symmetric for minority and non-minority borrowers. i.e., The matching threshold is the same for minority and non-minority borrowers because the payoff function is the same for minority and non-minority borrowers. I arrive at this conclusion using the standard game theory reasoning. Suppose that the matching threshold at lender j is higher for minority borrowers than for non-minority borrowers, then the marginal minority borrower k of lender j would deviate to other lenders. Other lenders would be happy to accept the minority borrower k because her rating is higher than their marginal borrowers (and being minority does not lower the total payoff to be shared). The potential deviation lowers the matching threshold for minority borrowers at lender j. In equilibrium, the market clears at the prices (transferred utilities) so that the matching threshold for minority and non-minority borrowers is the same for lenders of the same type.

However, the matching threshold is different for fintech lenders and banks. For the marginal borrower at fintech lenders Because the total payoff to be split is higher at fintech lenders (with θ), the prices (transferred utilities) are higher. The market clears at the prices so that the marginal fintech borrower is indifferent between using fintech lenders and banks so that no deviation to the other lender type happens. In addition, the marginal bank borrower is indifferent between having the loan or not.

Incentive compatibility constraints equalize the transferred utility (price) paid by the marginal borrower to fintech lenders and to banks. The wedge between the rating of the marginal borrower is determined by the additional utility parameter $h(\theta, \underline{\gamma_f})$.

Set outside opportunity to zero. The incentive compatibility constraints for the marginal borrower (i.e., at the thresholds) are,

$$g(\underline{\gamma_f}) + h(\theta, \underline{\gamma_f}) - p_f = g(\underline{\gamma_f}) - p_b \tag{D.1}$$

$$g(\underline{\gamma_b}) - p_b = 0 \tag{D.2}$$

Equation D.1 states that the marginal borrower at fintech lenders is indifferent between using fintech and banks. Equation D.2 states that the marginal borrower at banks is indifferent between having the loan or not.

This gives us,

$$p_f = h(\theta, \underline{\gamma_f}) + g(\underline{\gamma_b})$$

$$p_b = g(\underline{\gamma_b})$$

(1) For borrowers whose ratings are above $\underline{\gamma_f}$, their utility is

$$g(\gamma) + h(\theta, \gamma) - p_f = g(\gamma) + h(\theta, \gamma) - h(\theta, \underline{\gamma_f}) - g(\underline{\gamma_b}) \text{ if use fintech}$$

$$g(\gamma) - p_b = g(\gamma) - g(\underline{\gamma_b}) \text{ if use bank}$$

$\gamma > \underline{\gamma_f}$ and $\frac{\partial h(\theta_{i,j}, \gamma_i)}{\partial \gamma_i} > 0 \Rightarrow h(\theta, \gamma) - h(\theta, \underline{\gamma_f}) > 0$.
$\gamma > \underline{\gamma_f} > \underline{\gamma_b}$ and $g'(\gamma_i) > 0 \Rightarrow g(\gamma) - g(\underline{\gamma_b}) > 0$.
Therefore, $g(\gamma) + h(\theta, \gamma) - p_f = g(\gamma) + h(\theta, \gamma) - h(\theta, \underline{\gamma_f}) - g(\underline{\gamma_b}) > g(\gamma) - g(\underline{\gamma_b}) > 0$. Using fintech gives them higher utility and the utility is positive. They use fintech in equilibrium.

(2) For borrowers whose ratings are between $\underline{\gamma_b}$ and $\underline{\gamma_f}$, their utility is

$$g(\gamma) + h(\theta, \gamma) - p_f = g(\gamma) + h(\theta, \gamma) - h(\theta, \underline{\gamma_f}) - g(\underline{\gamma_b}) \text{ if use fintech}$$

$$g(\gamma) - p_b = g(\gamma) - g(\underline{\gamma_b}) \text{ if use bank}$$

$\gamma < \underline{\gamma_f}$ and $\frac{\partial h(\theta_{i,j},\gamma_i)}{\partial \gamma_i} > 0 \Rightarrow h(\theta,\gamma) - h(\theta,\underline{\gamma_f}) < 0$.
$\underline{\gamma_f} > \gamma > \underline{\gamma_b}$ and $g'(\gamma_i) > 0 \Rightarrow g(\gamma) - g(\underline{\gamma_b}) > 0$.
Therefore, $g(\gamma)+h(\theta,\gamma)-p_f = g(\gamma)+h(\theta,\gamma)-h(\theta,\underline{\gamma_f})-g(\underline{\gamma_b}) < g(\gamma)-g(\underline{\gamma_b})$ but $g(\gamma)-g(\underline{\gamma_b}) > 0$. Using banks gives them higher utility and the utility is positive. They use bank in equilibrium.

(3) For borrowers whose ratings are below $\underline{\gamma_b}$, their utility is

$$g(\gamma) + h(\theta,\gamma) - p_f = g(\gamma) + h(\theta,\gamma) - h(\theta,\underline{\gamma_f}) - g(\underline{\gamma_b}) \text{ if use fintech}$$

$$g(\gamma) - p_b = g(\gamma) - g(\underline{\gamma_b}) \text{ if use bank}$$

$\gamma < \underline{\gamma_b} < \underline{\gamma_f}$ and $\frac{\partial h(\theta_{i,j},\gamma_i)}{\partial \gamma_i} > 0 \Rightarrow h(\theta,\gamma) - h(\theta,\underline{\gamma_f}) < 0$.
$\gamma < \underline{\gamma_b}$ and $g'(\gamma_i) > 0 \Rightarrow g(\gamma) - g(\underline{\gamma_b}) < 0$.
Therefore, $g(\gamma) + h(\theta,\gamma) - p_f = g(\gamma) + h(\theta,\gamma) - h(\theta,\underline{\gamma_f}) - g(\underline{\gamma_b}) < g(\gamma) - g(\underline{\gamma_b}) < 0$. Using banks gives them higher utility but the utility is negative. They do not have loans in equilibrium.

To recap, we have a unique race-neutral equilibrium. Those borrowers with ratings above the threshold $\underline{\gamma_f}$ are matched with fintech lenders, while those with ratings between $\underline{\gamma_b}$ and $\underline{\gamma_f}$ are matched with banks. The matching threshold $\underline{\gamma_b}$ and $\underline{\gamma_f}$ are determined by the mass of lenders and borrowers.

4.2 Taste-Based Discrimination

4.2.1 Proof of Proposition 1

Set the difference between minority and non-minority borrowers for banks to zero. $p_{i,j}(\gamma_i,\theta_{i,j}) = g(\gamma_i)$ for both minority and non-minority borrowers matched with banks. For fintechs, the payoff function is $p_{i,j}(\gamma_i,\theta_{i,j}) = g(\gamma_i) + h(\theta^m,\gamma_i)$ for minorities and $p_{i,j}(\gamma_i,\theta_{i,j}) = g(\gamma_i) + h(\theta^n,\gamma_i)$ for non-minorities. Set the outside option of borrowers to zero. The equilibrium in this case is given by $(\underline{\gamma_{mf}}, \underline{\gamma_{mb}}, \underline{\gamma_{nf}}, \underline{\gamma_{nb}}, p_{mf}, p_{mb}, p_{nf}, p_{nb})$ that are determined by

$$M^m \int_{\underline{\gamma_{mf}}}^{\infty} f\left(x, \mu^m, \sigma^m\right) dx + M^n \int_{\underline{\gamma_{nf}}}^{\infty} f\left(x, \mu^n, \sigma^n\right) dx = M^f \tag{D.3}$$

$$M^m \int_{\underline{\gamma_{mb}}}^{\underline{\gamma_{mf}}} f\left(x, \mu^m, \sigma^m\right) dx + M^n \int_{\underline{\gamma_{nb}}}^{\underline{\gamma_{nf}}} f\left(x, \mu^n, \sigma^n\right) dx = M^b \tag{D.4}$$

$$g(\underline{\gamma_{mf}}) + h(\theta^m, \underline{\gamma_{mf}}) - p_{mf} = g(\underline{\gamma_{mf}}) - p_{mb} \tag{D.5}$$

$$g(\underline{\gamma_{nf}}) + h(\theta^n, \underline{\gamma_{nf}}) - p_{nf} = g(\underline{\gamma_{nf}}) - p_{nb} \tag{D.6}$$

$$g(\underline{\gamma_{mb}}) - p_{mb} = 0 \tag{D.7}$$

$$g(\underline{\gamma_{nb}}) - p_{nb} = 0 \tag{D.8}$$

$$p_{mf} = p_{nf} \tag{D.9}$$

$$p_{mb} = p_{nb} \tag{D.10}$$

Equations D.5 to D.8 are the incentive compatibility constraints for the marginal borrower in the minority-fintech, non-minority-fintech, minority-bank, and non-minority-bank matches respectively. Equations D.9 to D.10 are the lender's incentive compatibility.

$$(D.7) - (D.8) + (D.10) \Rightarrow g(\underline{\gamma_{mb}}) = g(\underline{\gamma_{nb}})$$

$$g'(\gamma) > 0 \Rightarrow \underline{\gamma_{mb}} = \underline{\gamma_{nb}} \tag{D.11}$$

$$(D.5) - (D.6) + (D.9) - (D.10) \Rightarrow h(\theta^m, \underline{\gamma_{mf}}) = h(\theta^n, \underline{\gamma_{nf}}) \tag{D.12}$$

Define the minority-non-minority rating gap in matching thresholds between fintech lenders and banks as $\underline{\Delta_{fintech-bank}\Delta_{minority-non-minority}} \stackrel{\text{def}}{=} (\underline{\gamma_{mf}} - \underline{\gamma_{nf}}) - (\underline{\gamma_{mb}} - \underline{\gamma_{nb}})$

$$(D.11) \Rightarrow \underline{\Delta_{fintech-bank}\Delta_{minority-non-minority}} = \underline{\gamma_{mf}} - \underline{\gamma_{nf}}$$

$$\frac{\partial h}{\partial\theta\partial\gamma} > 0 \text{ and } \theta^m > \theta^n \Rightarrow \underline{\gamma_{mf}} < \underline{\gamma_{nf}}$$

$$\text{Therefore, } \underline{\Delta_{fintech-bank}\Delta_{minority-non-minority}} = \underline{\gamma_{mf}} - \underline{\gamma_{nf}} < 0 \text{ iff } \theta^m > \theta^n$$

4.2.2 Extension on Additional Utility for Banks

The key prediction that $\Delta_{fintech-bank}\Delta_{minority-non-minority}$ is negative if fintech lenders are less discriminating does not depend on the simplification assumption on no additional utility component in payoff functions for banks. In this section, I extend the payoff function of matches with banks. It also helps to understand that the rating-gap prediction does not depend on no gap in borrowers matched with banks (D.11), which is clearly too strong to reflect the reality. Rather, (D.11) is only a notation-saving simplification. In other words, the proof in this section motivates why the main prediction to test is the double difference $\Delta_{fintech-bank}\Delta_{minority-non-minority}$ instead of two first differences $\Delta_{minority-non-minority}$ for fintech and for banks.

$p_{i,j}(\gamma_i, \theta_{i,j}) = g(\gamma_i) + h(\theta^{mb}, \gamma_i)$ for minority borrowers who have been paired with traditional lenders. $p_{i,j}(\gamma_i, \theta_{i,j}) = g(\gamma_i) + h(\theta^{nb}, \gamma_i)$ for non-minority borrowers who have been paired with traditional lenders. $p_{i,j}(\gamma_i, \theta_{i,j}) = g(\gamma_i) + h(\theta^{mf}, \gamma_i)$ for minority borrowers paired with fintech lenders. $p_{i,j}(\gamma_i, \theta_{i,j}) = g(\gamma_i) + h(\theta^{nf}, \gamma_i)$ for non-minority borrowers paired with fintech lenders. $g' > 0$, $\frac{\partial h}{\partial\gamma} > 0$, and $\frac{\partial h}{\partial\theta\partial\gamma} > 0$.

Fintech lenders are less discriminating against minority borrowers means that the utility gain for minorities is larger at fintech than at banks. $\theta^{mf} - \theta^{nf} > \theta^{mb} - \theta^{nb}$. The equivalence of Proposition 1 under this extension is $\underline{\gamma_{mf}} < \underline{\gamma_{nf}}$, $\underline{\gamma_{mb}} > \underline{\gamma_{nb}}$ iff $\theta^{mf} > \theta^{nf}$, $\theta^{mb} < \theta^{nb}$.

Here is the proof. The incentive compatibility constraints are,

$$g(\underline{\gamma_{mf}}) + h(\theta^{mf}, \underline{\gamma_{mf}}) - p_{mf} = g(\underline{\gamma_{mf}}) + h(\theta^{mb}, \underline{\gamma_{mf}}) - p_{mb} \tag{D.13}$$

$$g(\underline{\gamma_{nf}}) + h(\theta^{nf}, \underline{\gamma_{nf}}) - p_{nf} = g(\underline{\gamma_{nf}}) + h(\theta^{nb}, \underline{\gamma_{nf}}) - p_{nb} \tag{D.14}$$

$$g(\underline{\gamma_{mb}}) + h(\theta^{mb}, \underline{\gamma_{mb}}) - p_{mb} = 0 \tag{D.15}$$

$$g(\underline{\gamma_{nb}}) + h(\theta^{nb}, \underline{\gamma_{nb}}) - p_{nb} = 0 \tag{D.16}$$

$$p_{mf} = p_{nf} \tag{D.17}$$

$$p_{mb} = p_{nb} \tag{D.18}$$

$$(D.13) - (D.14) + (D.17) - (D.18) \Rightarrow h(\theta^{mf}, \underline{\gamma_{mf}}) - h(\theta^{mb}, \underline{\gamma_{mf}}) = h(\theta^{nf}, \underline{\gamma_{nf}}) - h(\theta^{nb}, \underline{\gamma_{nf}})$$

$$(D.15) - (D.16) + (D.18) \Rightarrow g(\underline{\gamma_{mb}}) + h(\theta^{mb}, \underline{\gamma_{mb}}) = g(\underline{\gamma_{nb}}) + h(\theta^{nb}, \underline{\gamma_{nb}})$$

$g' > 0$ and $\frac{\partial h}{\partial \gamma} > 0 \Rightarrow \underline{\gamma_{mb}} > \underline{\gamma_{nb}}$ iff $\theta^{mb} < \theta^{nb}$.

$\frac{\partial h}{\partial \theta \partial \gamma} > 0 \Rightarrow \underline{\gamma_{mf}} < \underline{\gamma_{nf}}$ iff $\theta^{mf} > \theta^{nf}$, $\theta^{mb} < \theta^{nb}$.

In this extension, while matching thresholds (D.11) at banks are relaxed to more realistic representation $\underline{\gamma_{mb}} > \underline{\gamma_{nb}}$, the key prediction on the double difference in rating does not change. $\Delta_{fintech-bank}\Delta_{minority-non-minority}$ is negative if fintech lenders are less discriminating against minority borrowers.

4.2.3 Proof of Corollary 1

$$
\begin{aligned}
E(\Delta\Delta|\cdot) &\stackrel{\text{def}}{=} \left[\mathbb{E}\left(x|x \geq \underline{\gamma_{mf}}, \mu^m, \sigma^m\right) - \mathbb{E}\left(x|x \geq \underline{\gamma_{nf}}, \mu^n, \sigma^n\right)\right] \\
&\quad - \left[\mathbb{E}\left(x|\underline{\gamma_{mb}} \leq x < \underline{\gamma_{mf}}, \mu^m, \sigma^m\right) - \mathbb{E}\left(x|\underline{\gamma_{nb}} \leq x < \underline{\gamma_{nf}}, \mu^n, \sigma^n\right)\right] \\
&= \left[\mu^m + \sigma^m \frac{\varphi(\frac{\underline{\gamma_{mf}}-\mu^m}{\sigma^m})}{1-\Phi(\frac{\underline{\gamma_{mf}}-\mu^m}{\sigma^m})} - \sigma^n \frac{\varphi\left(\frac{\underline{\gamma_{nf}}-\mu^n}{\sigma^n}\right)}{1-\Phi(\frac{\underline{\gamma_{nf}}-\mu^n}{\sigma^n})}) - \mu^n\right] \\
&\quad - \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)} - \sigma^n \frac{\varphi\left(\frac{\underline{\gamma_{nb}}-\mu^n}{\sigma^n}\right) - \varphi\left(\frac{\underline{\gamma_{nf}}-\mu^n}{\sigma^n}\right)}{\Phi\left(\frac{\underline{\gamma_{nf}}-\mu^n}{\sigma^n}\right) - \Phi\left(\frac{\underline{\gamma_{nb}}-\mu^n}{\sigma^n}\right)} - \mu^n\right] \\
&= \sigma^m \left[\frac{\varphi(\frac{\underline{\gamma_{mf}}-\mu^m}{\sigma^m})}{1-\Phi(\frac{\underline{\gamma_{mf}}-\mu^m}{\sigma^m})} - \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] \\
&\quad - \sigma^n \left[\frac{\varphi\left(\frac{\underline{\gamma_{nf}}-\mu^n}{\sigma^n}\right)}{1-\Phi(\frac{\underline{\gamma_{nf}}-\mu^n}{\sigma^n})} - \frac{\varphi\left(\frac{\underline{\gamma_{nb}}-\mu^n}{\sigma^n}\right) - \varphi\left(\frac{\underline{\gamma_{nf}}-\mu^n}{\sigma^n}\right)}{\Phi\left(\frac{\underline{\gamma_{nf}}-\mu^n}{\sigma^n}\right) - \Phi\left(\frac{\underline{\gamma_{nb}}-\mu^n}{\sigma^n}\right)}\right]
\end{aligned}
\tag{D.19}
$$

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

Suppose that the underlying distribution is the same for minority and non-minority borrowers, i.e.,$\mu^m = \mu^n = \mu$ and $\sigma^m = \sigma^n = \sigma$, combined with(D.11) $\underline{\gamma_{mb}} = \underline{\gamma_{nb}} = \sigma\tilde{\gamma} + \mu$, (D.13) becomes,

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

Using the symmetricity of normal distribution,

$$G(x) = \frac{\varphi(x)}{1-\Phi(x)} - \frac{\varphi(\tilde{\gamma}) - \varphi(x)}{\Phi(x) - \Phi(\tilde{\gamma})} = \frac{\varphi(x)}{\Phi(-x)} + \frac{\varphi(x) - \varphi(\tilde{\gamma})}{\Phi(x) - \Phi(\tilde{\gamma})}$$

Internet Appendix E: Empirical Matching Model Estimation Setup

The computational costs of estimating the Fox (2018) model increase rapidly with the number of parameters. Therefore, I only include covariates that are closely related to the borrower-lender matching process but exclude most of the control variables from the regression analysis. For the same purpose, I group three minority indicators into one group: minority borrowers. As discussed in the model assumptions, only characteristics of the matched pair that are related to both borrowers and lenders enter the value function in the estimation. In addition, following the literature (Chen and Song (2013), Akkus et al. (2016), Schwert (2018)), I demean all borrower and lender characteristics so that their interactions can be interpreted as covariances.

I include the following five covariates. First, the covariate of interest in the matching value function is the product of the fintech lender indicator and the minority borrower indicator. It enters the matching value function as the analog to the coefficient on the minority borrower dummies in Table 2. A positive coefficient on the product term between the fintech lender and the minority borrower indicators means that more value is generated by matching fintech lenders with minority borrowers, whereas a negative coefficient means that more value is generated by matching fintech lenders with non-minority borrowers. I refer to this as the additional value channel of fintech lenders to minority borrowers.

Second, to account for relationship persistence, I include an indicator for whether there is an SBA loan between the borrower and the lender during 2009-2019. Third, for the bank desert channel, I include a variable on the number of active bank branches of the lender in 2020 in the zip code region of the borrower. For fintech lenders, I set the number to the maximum in my sample (11) because the online service is likely to easily accessible for every region. Fourth, as previous studies show the importance of geographic distance in banking (Granja et al. (2022a)), I also include a covariate on the mile distance between the borrower and the lender headquarters. Because the effective distance to use fintech lenders is tiny, I set the geographic distance to zero when the match is formed with fintechs. Firth, restaurant rating is an important confounding factor, as higher-rated restaurants can be more likely to self-select into fintech users. To account for sorting by rating, I include the product of the fintech lender indicator and the borrower's rating.

Without data on the transfer payments, identification is only up to arbitrary order-preserving transformations of the parameters (Manski (1975)). A scale normalization on the parameter vector is needed. I fix the scale (bounds in the differential evolution optimization) to ± 4000 and choose the parameters that satisfies a greater percentage of the pairwise stability inequalities. 4000 is chosen based on sensitivity analysis on the bounds.

As in the regression analysis, I treat the 2020 and 2021 PPP as two samples, which gives separate matching markets. Due to computational power limitations, I restrict to state-by-state estimation. I report the average of all 51 states.[4] The observed matches are the matching between borrowers and lenders that occurred in the PPP. Inequalities are generated by swapping every observed pair of borrower-lender matches in the same state, with the restriction that the lender lent at least one PPP loan in the same city as the borrower. This restriction lowers the total number of inequalities and computational demand.

[4]The 2021 PPP sample of 400,814 inequalities can be coped with cloud computation. I report results using the full 2021 sample in the Internet Appendix, which shows the same sign and the same relative magnitude as to the average across states. Even restricted to within-state swapping of borrower-lender matches, the 2020 PPP sample contains more than 109 million inequalities which require memory impossible with the current computer power. Another attempt is to restrict to a small random sample. The issue here is if the sample is too small, it loses many interactions among players, which gives imprecise estimations.