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Using Technology to Tackle Discrimination in Lending: The Role of Fintechs in the Paycheck Protection Program[†]

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A well-established literature documents worse lending outcomes for Black borrowers than White borrowers (Blanchflower, Levine, and Zimmerman 2003; Fairlie, Robb, and Robinson 2020). One possible explanation for this disparity is that lenders traditionally rely on soft information gleaned from personal relationships with potential borrowers. Black borrowers may face greater barriers to establishing these relationships (Bates and Robb 2015), and lenders may relate differently to Black and White borrowers by requiring more or different information to facilitate lending (Bone et al. 2019). If so, then financial tools that rely less on soft information should reduce differences in lending outcomes for Black and White borrowers. For example, Chatterji and Seamans (2012) find that the introduction of credit cards in the late 1970s and early 1980s helped to increase both Black and White entrepreneurship but that the effect was especially pronounced for Black entrepreneurs who had fewer options to obtain capital necessary for starting and maintaining a business. New technology-based financial lending tools have the potential to likewise increase entrepreneurship by expanding access to capital. Indeed, Bartlett et al. (2019) find early evidence that algorithmic lending expands competition and increases shopping behavior among borrowers in consumer markets.

In this paper, we study lending by fintechs. Philippon (2016) defines fintechs as "digital innovations and technology-enabled business model innovations in the financial sector." Fintech firms rely on "hard" data about loan applicants together with sophisticated algorithms to make lending decisions. Given that fintechs rely more on algorithms and less on soft information than traditional banks do, we would expect to observe fewer Black and White disparities in lending outcomes, which could include loan applications, loan approval, or loan amounts. Howell et al. (2021) show that when small banks automated their lending processes, loan approval rates to Black-owned businesses increased relative to small banks that did not automate. Note that there may still be differences, to the extent that discrimination is encoded in the data used by the algorithms. Evidence from fintech lending in mortgage markets shows that despite missing self-reported data on an applicant's race, information collected for scoring or pricing loans is significantly correlated with race (Bartlett et al. 2019).

To study this issue, we take advantage of new data on Paycheck Protection Program (PPP) loans. The PPP was one of the many policy interventions by the US government during the COVID-19 pandemic. We focus on the first two rounds of PPP, which ran between April 10, 2020, and August 8, 2020, and provided nearly 5.2 million loans through nearly 5,500 lenders totaling $525 billion for small businesses (those with 500 employees or less) that could be used for operating expenses including payroll, mortgage interest or rent, utilities, and approved expenses. Atkins, Cook, and Seamans (2022) provide more detail on the PPP program and describe several other papers that have investigated how design features and other institutional details of the PPP program affected Black-owned businesses.

We find that PPP loans from the top-five largest commercial banks to Black borrowers are approximately 59 percent smaller than those to observationally similar White borrowers. On the

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other hand, PPP loans from fintechs to Black borrowers are approximately 13 percent smaller than those to observationally similar White borrowers. Our results suggest that fintech models may reduce some but not all of the Black–White disparities in small business lending outcomes.

I. Data

Data on individual PPP loans come from the Small Business Administration (SBA). The PPP-loan-level data provide us with information about the size of the loan, our main dependent variable. We use this dependent variable to study how race affects loan size by comparing differences in the sizes of loans to Black and White borrowers. As reported by Atkins, Cook, and Seamans (2021), loan amounts are highly skewed. In addition, some of the loan amounts appear to have been recorded incorrectly with values such as "0" or "1." To address these issues, we winsorize the loan amounts (any loan less than \$1,000 is coded as \$1,000, and any loan more than \$1.5 million is coded at \$1.5 million) and take the natural log of the loan amount. We include a number of other loan-level and zip-code-level variables as controls.

Summary statistics of the variables are reported in Atkins, Cook, and Seamans (2022). There are approximately 4.5 million loans in the full sample. Most loan recipients did not report race (unanswered race of owner is about 90 percent). As indicated by Atkins, Cook, and Seamans (2021), there are some notable differences between the full sample and the subsample of loans that report race, suggesting that there is a selection issue. Garcia and Darity (forthcoming) highlight some of the strategic reasons businesses owners may not report race. We address selection issues using a Heckman selection approach, described in more detail in Atkins, Cook, and Seamans (2021).

II. Results

In Table 1, we report results from a series of regressions using the data described above. The regressions are of the following form:

$$(1)\ \ln(loan\ amount_{iz}) = \beta_0 + \beta_1 Black_i + \beta_2 White_i + \mathbf{X}_{iz}\mathbf{B} + \varepsilon_{iz}$$

Table 1—Loan-Level Results

Dependent variable: Ln (*Loan amount*)	Full sample (1)	Top-five commercial banks (2)	Fintech leaders (3)
Asian owner	0.022	−0.047	0.011
	[0.005]	[0.029]	[0.029]
Black owner	−0.162	−0.255	0.285
	[0.009]	[0.068]	[0.041]
Hispanic owner	0.089	0.130	0.212
	[0.006]	[0.035]	[0.034]
White owner	0.357	0.332	0.414
	[0.002]	[0.020]	[0.021]
Other race owner	−0.298	−0.408	−0.762
	[0.098]	[0.311]	[0.315]
Zip code demographics	Yes	Yes	Yes
Loan characteristics	Yes	Yes	Yes
Corporate form dummies	Yes	Yes	Yes
Two-digit NAICS dummies	Yes	Yes	Yes
State dummies	Yes	Yes	Yes
Mills ratio	Yes	Yes	Yes
Observations	4,403,709	780,367	568,318
R^2	0.34	0.27	0.19

Sources: SBA, authors' calculations

for loan recipient i in zip code z. The dependent variable, *loan amount*, has been transformed as has been described above. The main independent variables of interest are *Black*, an indicator for whether the loan recipient self-reported as Black, and *White*, an indicator for whether the loan recipient self-reported as White. We include a variety of other control variables in $\mathbf{X}$, including dummy variables for other races, gender, veteran status, jobs reported, and dummy variables for industry (at the two-digit North American Industry Classification System (NAICS) code level) and state. The results are clustered by zip code.

To assess the role played by fintech lenders, we separately run regressions for fintech lenders and top-five commercial banks, and then we assess differences in the coefficients on Black and White in equation (1) across these subsamples. The list of fintech lenders comes from Howell et al. (2021). The top-five commercial banks are Bank of America, Chase, Citibank, US Bank, and Wells Fargo.

To assess the difference between Black and White borrowers, we can assess the difference between the coefficients on these two variables. We first look at results using the full sample in column 1. The coefficient on Black is

−0.162; the coefficient on White is 0.357. The difference is approximately 0.519, suggesting that loans to Black borrowers were almost 52 percent lower than those to observationally similar White borrowers. Next, we look at results using the subsample of loans from top-five commercial banks in column 2. The coefficient on Black is −0.255; the coefficient on White is 0.332. The difference is approximately 0.587, suggesting that loans from top-five banks to Black borrowers were almost 59 percent lower than those to observationally similar White borrowers. In column 3, we present results using the subsample of loans from fintech firms. The coefficient on Black is 0.285; the coefficient on White is 0.414. The difference is approximately 0.129, suggesting that loans from fintechs to Black borrowers were almost 13 percent lower than those to observationally similar White borrowers. Comparing the results across columns 2 and 3, it appears that loans to Black borrowers were systematically lower than those to observationally similar White borrowers, regardless of type of lender. However, the difference shrinks noticeably when the lender is a fintech relative to a top-five commercial bank. Atkins, Cook, and Seamans (2022) provide a variety of additional results and robustness tests. The results are similar across all these specifications.

III. Conclusion

Our analysis suggest that fintech models may reduce some but not all of the Black–White disparities in small business lending outcomes. Future research is needed to confirm whether replacing human relationships with computer algorithms facilitated this reduction. That disparities persist, though in reduced form, presents challenges and opportunities for policymakers, regulators, and the broader financial services industry. It suggests that antidiscrimination law monitoring and enforcement should be expanded in ways that address the unique operating features of fintechs. But regulations should be implemented in ways that amplify the potential societal benefits that fintechs can offer through increased competition in financial markets and expanded, more equitable access to small business finance.

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