Racial Discrimination in Entrepreneurship: Decomposing Demand and Supply *

Eugene Tan†, Teegawende H. Zeida‡

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Abstract

Using micro-data on startups, we find that Black-owned (relative to White-owned) startups operate with lower capital intensity and have lower average returns to capital. We formulate a theoretical framework showing that these findings are consistent with the hypothesis that Black entrepreneurs face both consumer (demand) and financial (credit supply) discrimination. We further show that the differences in capital returns are persistent over time, whereas the differences in capital intensity disappear after four years. This indicates that any negative effects of financial discrimination are transitory, but demand-side discrimination can permanently reduce the profitability of Black-owned firms. Our results provide a complementary explanation for the persistent racial wealth gap despite efforts to reduce discrimination in credit markets.

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†University of Toronto. Email: eugene.tan@rotman.utoronto.ca.
‡Brock University. Email: tzeida@brocku.ca.
1 Introduction

The large and persistent difference in wealth between White and Black households has led policymakers to propose programs to address this issue. Of particular interest to policymakers is the potential to foster wealth generation via entrepreneurship (e.g. Fact Sheet (2021) of the Biden-Harris Administration).\(^1\) In part, this builds on the belief that Black entrepreneurs face race-based barriers to running a profitable business. A primary focus has been placed on addressing differential access to capital; in other words, the focus has been on studying discrimination in the supply of productive factors. In contrast, while substantial research has uncovered consumer discrimination against racial minorities in specific markets (such as cellphone retailers), little focus has been placed on studying demand-side discrimination as a more general barrier to successful Black entrepreneurship. In this paper, we study whether, in addition to financial discrimination, demand-side discrimination might also be an important barrier of profitability for Black entrepreneurship, and consequently, whether public policies aimed at addressing such disparities might also be important.

To answer our question, we first present a simple theoretical framework incorporating non-constant demand elasticities (i.e., non-constant markups) that will be useful in uncovering the existence of race-based demand discrimination. Our key prediction is that, holding all else equal, if Black entrepreneurs faced demand-side discrimination, then Black-owned firms would operate with lower average revenue products of capital (ARPK)—that is, lower average returns to capital—relative to White entrepreneurs. This result derives from the intuition that if Black entrepreneurs were discriminated against by consumers, then they would only be able to charge a lower price relative to White entrepreneurs for the same exact product.\(^2\) We then test this hypothesis using firm-level panel data in the United States, which tracks various key characteristics of a single-cohort of startup firms from formation in 2004 through to 2011. We find that, as a headline number, Black firms report around 0.373 log-points lower ARPK rela-

\(^1\)For more details, go to www.whitehouse.gov.

\(^2\)To be precise, when we refer to “demand-side discrimination”, we refer to the inability for a Black business owner to charge the same price as a White business owner for the same product. Such differences can arise for a multitude of reasons. For instance, because end-users have different preferences for purchasing goods or services from a Black or White operated business in business-to-consumer transactions, or because Black business owners have smaller bargaining power relative to White business owners in business-to-business transactions. In our framework, we attribute all these differing reasons to a generic “demand-side” discrimination.
tive to White entrepreneurs, implying that on average, the average returns to capital of Black-owned firms is about two-thirds that of White-owned firms. Our results are robust to various controls that proxy for wealth and human capital accumulation.

Our empirical finding is striking in light of the standard assumptions adopted by the macroeconomics literature on capital misallocation. Specifically, the standard framework typically assumes either constant elasticities of demand or a competitive environment, and consequently predicts that credit-constrained firms operate with higher ARPK, with the intuition being that constrained firms are under-capitalized. Taking this interpretation to our data, a corollary would be that Black-owned firms enjoy a capital subsidy relative to White-owned firms—a stark result compared to the underlying assumption of discrimination against Black entrepreneurs.

In contrast, our framework emphasizes that the preceding prediction is a special case that arises specifically because markups are assumed constant (or zero); as a consequence, demand-side discrimination does not directly affect the level of ARPK. Instead, we show that for a more general framework with non-constant markups, the level of ARPK is determined by both the cost of capital and demand-side factors. Importantly, individuals facing demand-side discrimination have lower market power, and consequently lower “revenue productivity” (Foster et al. (2008)), and in turn operate with lower ARPK. Consequently, our empirical finding is indicative of either discrimination on the demand-side, or a capital subsidy.

To further elucidate the underlying driver of our finding, we further test for differences in capital intensity across the two groups. Using our framework, we show that the capital-labor ratio, a measure of capital intensity, is independent of markups, and inversely proportional to the cost of capital. Therefore, firms facing financial discrimination will operate with lower capital intensity, but firms facing only demand-side discrimination would operate with the same capital intensity as non-discriminated firms. Accordingly, this statistic is useful in detecting whether Black-owned firms do indeed face tighter financial constraints. Our baseline regression specification suggests that this is indeed the case, with Black-owned firms operating an average 0.522 log-points lower capital-labor ratio.

Taken together, our results suggest that, on average, Black entrepreneurs face tighter credit constraints, but that discrimination on the consumer side could poten-
tially be larger, thus giving rise to lower average returns to capital. To investigate
the differential severity of the two channels, we next exploit the time-series dimension
of our data set. As is well known, if firm productivity is persistent, then a finan-
cially constrained firm will eventually grow out of their constraints through asset
accumulation (e.g., Moll (2014)). This self-financing channel implies that, if financial
discrimination is the key dominating factor, then differences in ARPK and capital in-
tensity would fade out over time. Critically, the rate of convergence would be a good
proxy for the degree of financial discrimination relative to consumer discrimination.
In contrast, to the extent that demand-side discrimination is constant, a reasonable
assumption especially given the length of our data, differences in ARPK would persist
across time, since individuals cannot alleviate this constraint independently.

As in our prediction, we find in the data that the difference in capital-labor ratio
between Black and White firms rapidly narrows four years into firm formation. This
suggests that despite the initial differential access to capital, high-productivity Black
entrepreneurs quickly accumulate enough wealth to outgrow their disadvantage. In
contrast, we find that the ARPK differences are persistent across time, and in partic-
ular, consistent over the same four years from founding. As we argued, this provides
further evidence that demand-side discrimination is active and dominant.

While we do not directly explore the quantitative effects of these differences, in
part driven by a lack of suitable data to do a rigorous quantitative analysis, our results
suggest that demand-side differences might play a large role in driving the persistent
racial wealth gap. Noticeably, the disadvantage in capital access appear to fade out
after four years, implying that discrimination in financial access is unlikely to be a
dominant role in multi-generational disparities in wealth accumulation. Our findings
therefore shed some light on the source of wealth disparities, suggesting that policy
tools based solely on financing are unlikely to close the racial wealth gap. In contrast,
policy tools aimed at addressing demand disparities might be a more effective way in
closing the racial wealth gap.4

The rest of the paper is structured as follows. After the literature review, we
present in Section 2 our theoretical framework emphasizing the importance of ac-
counting for non-constant markups when studying discrimination on both the supply

4For instance, in a recent June 1 2021 statement by the Biden administration, the federal gov-
ernment has committed to growing federal contracting with small disadvantaged businesses by 50
percent. For more details, go to www.whitehouse.gov.
and demand side. Following that, in Section 3, we present our main empirical results utilizing a cross-sectional analysis, and in Section 4, we further present and discuss results exploiting our panel dimension. We then conclude our paper in Section 5.

1.1 Related Literature

Our paper is related to both the broader literature on racial discrimination and the macroeconomics literature on factor misallocation.

First, our paper adds to the growing body of evidence documenting the presence of demand or consumer discrimination against racial minorities. For example, Borjas and Bronars (1989) show that the income distribution of Black and White business owners in the 1980 US Census is consistent with a theory of consumer discrimination. More recently, a substantial body of direct empirical evidence has also buttressed this view. For instance, Leonard et al. (2010) show that retailers with a larger number of Black employees in regions with a larger White population tend to suffer lower sales. Likewise, recent research documented that Black online vendors charge lower prices for identical goods (e.g., Doleac and Stein (2013) on E-bay transactions, Edelman and Luca (2014) and Kakar et al. (2018) on AirBnB). Our key empirical result, emphasizing demand-side discrimination, is consistent with these earlier findings. Importantly, we also document the persistence of demand-side discrimination and its impact on the profitability, and propose a link from this observation to the persistent racial wealth gap.

Second, our paper also contributes to the literature on financial discrimination against racial minorities. Our paper is most directly related to the literature document- ing financial discrimination against Black-owned firms (e.g., Robb et al. (2009); Chatterji and Seamans (2012); Bates and Robb (2015); Fairlie et al. (2020); Kim et al. (2021) and Brown et al. (2022)). Of particular note is Fairlie et al. (2020), which documents similar findings, in terms of financial discrimination, using the same dataset. Unlike these papers, we emphasize our results through a macroeconomic framework, which allows us to uncover the presence of consumer discrimination. In turn, this allows us to emphasize the role of demand-side discrimination, as opposed to financial discrimination, in driving the persistence of a profitability gap between Black-owned and White-owned firms. In this dimension, our emphasis is similar to recent research emphasizing the importance of group-based demand-side discrimination (Hardy and


Third, our paper adds to the macroeconomics literature on factor misallocation, and in particular, misallocation driven by discrimination. Our contribution is both technical and empirical. On the methodology dimension, we show that standard assumptions in the misallocation literature (e.g., Hsieh and Klenow (2009)) can generate misleading conclusions regarding the credit constraints of a firm because it predicts an unconditional correlation between the average returns to capital and credit constraint tightness. We show how a simple extension of this standard framework to allow for non-constant elasticities of demand can bypass this issue. On the empirical dimension, we add to the small but growing literature in macroeconomics studying the impact of discrimination on aggregate outcomes (e.g., Hsieh et al. (2019); Bento and Hwang (2021) and Bento and Hwang (2022)).

Finally, our paper contributes to ongoing macroeconomics research into the sources of the racial wealth gap in the United States. Recent research (e.g., Derenoncourt et al. (2021) and Aliprantis et al. (2021), among others) have documented a large and persistent gap in wealth between Black and White households, and in addition, find that a substantial driver of this gap is a permanent difference in earnings and returns to investment. Our paper is complimentary to theirs, by documenting that Black entrepreneurs have a persistently lower average returns to capital. Moreover, we also attempt to uncover the source of this difference, arguing that the persistent return differences are driven by demand-side discrimination. In contrast, our findings differ from the recent hypothesis put forth in Boerma and Karabarbounis (2021), who argue that Black entrepreneurs underinvest in their own businesses due to pessimistic beliefs about returns on investment, rather than actual differences.

2 Theoretical Framework

In this section, we present our theoretical framework which motivates our analysis in Section 3.

Such findings are also consistent with recent research in the sociology literature documenting a negative bias in appraisal values of Black-owned houses, which in turn implies a lower return to housing investment (e.g., Howell and Korver-Glenn (2021)).
2.1 Model Setup

We assume that there is a population of firms in the economy. Each firm is run by an individual $i$ who belongs to a group $g \in \{W, B\}$, where $W$ and $B$ stand for White and Black firms respectively. Firms face a generic revenue generating function given by $p(y_i, d_i, \tau^d_g) y_i$, where $p(\cdot)$ is the inverse demand function that depends on individual $i$-specific demand characteristics $d_i$, physical output $y_i$ produced by the individual firm, as well as a group-specific fixed effect $\tau^d_g$ that determines the revenue productivity of the firm. We will maintain the following assumptions for the rest of the paper,

**Assumption 1. (Revenue)** The inverse demand function is strictly increasing in $d_i$ and $\tau^d_g$, decreasing in $y_i$, and smooth almost everywhere. Moreover, the price elasticity of demand is weakly increasing in prices.

Our assumption implies that all firms face some amount of market power, and thus face downward sloping demand curves. We assume that $d_i$ and $\tau^d_g$ can be ranked, such that higher values correspond to higher demand for individual $i$’s or group $g$’s product. Importantly, we do not assume any specific market structure, so long as the given market structure is consistent with a downward sloping demand curve, and that the super-elasticity of demand is non-negative.

**Assumption 2. (Production)** Output $y$ is produced using a production function with a constant elasticity of substitution (CES) and constant returns over two factors of inputs, capital ($k$) and labor ($l$). The factors are rented or hired on a spot market, where their external costs are $r$ and $w$ respectively, whereas the firm faces implicit cost of capital given by $(1 + \tau^r_g)r$. All entrepreneurs have the same productivity in producing physical output.

**Assumption 3. (Uncertainty)** There is no uncertainty associated with firm production or demand.

Our assumption on production choices and uncertainty follow the spirit of Hsieh and Klenow (2009). In this context, higher $\tau^r_g$ implies that firms from group $g$ face higher implicit costs of capital. For instance, if Black entrepreneurs faced financial discrimination, be it because they are charged higher interest rates (explicit) or face higher probabilities of loan denials (implicit), then this effect would be captured in a
relatively higher \( \tau_g^r \). Moreover, we are also assuming that labor costs are homogeneous across firms, which we assume for ease of exposition, since we are focusing our study on capital frictions.

Given our notation, the firm’s static profit function is given by

\[
\pi = p(y, d, \tau_g^d)y - (1 + \tau_g^r)rk - wl, \tag{1}
\]

where we suppress the subscript \( i \) for notational ease. We now derive three formal relationships. For the rest of the paper, all derivations and proofs are relegated to Appendix A.

First, a profit-maximizing firm always sets its marginal revenue product of capital (MRPK) to its implicit cost of capital, given by the following equation,

\[
MRPK = (1 + \tau^r)r. \tag{2}
\]

Importantly, this is true regardless of market structure. This implies that a direct measurement of a firm’s MRPK is directly revealing of the firm’s cost of capital, and thus extent of discrimination. However, because direct measurement of MRPK is essentially impossible, researchers typically operationalize this insight by using the average revenue product of capital (ARPK) as a proxy. Our second derivation relates ARPK to MRPK through the following formula,

\[
\log ARPK = \log MRPK + \log (1 + \mu (\tau_g^d, d; \tau_g^r)) - \log \epsilon_k. \tag{3}
\]

Here, \( \mu \) is the markup of the firm, which depends on the market structure (and hence the revenue generating function). \( \epsilon_k \) is the elasticity of physical output with respect to capital, and arises only from the production side of the equation.

Finally, the capital-labor ratio is given by the following formula

\[
\log \frac{k}{l} = \log \epsilon_{k,l} - \log r - \log (1 + \tau^r) + \log w. \tag{4}
\]

Here, \( \epsilon_{k,l} \) is an elasticity term capturing the marginal rate of technical substitution for a given level of output. Like \( \epsilon_k \), this arises entirely from the production side of the equation.

With these relationships, we can then derive a simple result in relation to the
elasticity terms as summarized below.

Lemma 1. If Assumptions 1-3 hold, then the elasticity terms, $\epsilon_k$ and $\epsilon_{k,l}$, are functions of only $r$, $w$, and $\tau_{g}$, and in particular, increasing in $\tau_{g}$. Moreover, and consequently, they do not directly depend on the market structure.

With our results in hand, we can now present our main result in a formal proposition:

Proposition 1. If Assumptions 1-3 hold, then as a result of Lemma 1, (i) differences in the capital-labor ratio across groups are driven only by differences in $\tau_{g}$, that is, access to financing; (ii) differences in ARPK across groups are driven by both differences in $\tau_{g}$ and $\tau_{d}$, that is, they depend on both access to financing and demand. Moreover, holding all else constant, increases in $\tau_{g}$ (i.e., discrimination in access to financing) increases both ARPK and the capital-labor ratio, while decreases in $\tau_{d}$ (i.e., discrimination in demand) reduces ARPK but has no effect on the capital-labor ratio.

An important corollary of our proposition is then that differences in ARPK across groups are not useful in detecting financial discrimination because they conflate the effects of both demand- and supply- side discrimination. Crucially, it is possible for firms to operate with lower average returns to capital even when they suffer from financial discrimination, if discrimination on the demand side is sufficiently high. In contrast, differences in the capital-labor ratio is useful for detecting financial discrimination because this statistic is not contaminated by demand-side differences. Consequently, when both statistics are used jointly, one could in principle decompose both demand- and supply- side discrimination. In the empirical section, we will exploit these results into understanding the extent to which Black entrepreneurs face these two sources of discrimination.

2.2 Connecting Our Framework to Standard Models

Before we turn to the empirical results, we now connect our model to the standard framework in the macroeconomics misallocation literature. Our goal is to emphasize that such a framework can lead to misleading conclusions regarding financial discrimination if a researcher overly emphasizes differences in ARPK across groups.
To elucidate, the standard framework borrows from the assumptions of Hsieh and Klenow (2009), and is nested as a special case of our model. Specifically, the assumptions are (i) physical production is Cobb-Douglas, and (ii) markups are constant (or zero for perfectly competitive models). The first assumption is nested within our CES production framework, and is innocuous. The key issue lies with the markup assumption. Specifically, as we see from equation 3, a constant markup assumption implies that demand-side differences do not show up in measures of ARPK. In other words, Black-owned firms, as long as they face financial discrimination, must always operate with higher ARPK. Conversely, if they operate with lower ARPK, we would always conclude they face a capital subsidy. As we will now show, such an unconditional prediction makes it a challenge for this framework to rationalize our empirical findings.

3 Racial Discrimination in Entrepreneurship — Cross-Sectional Facts

In this section, we introduce our data source and report our key empirical findings.

3.1 Data Source

Our data source draws from the Kauffman Firm Survey (KFS). The KFS is a single-cohort panel survey consisting of firms that were formed in the year 2004 and tracked through 2011. The universe of firms considered for survey inclusion consisted of all newly registered firms in 2004 from the Dun and Bradstreet database, followed by a series of conditions. The KFS is a large survey and provides extensive details on survey respondents. For the purposes of our paper, we focus on the revenue, assets, employment of the firm, as well as the race of the primary owner. Importantly, the latter variable is not typically available in most firm-level data. Descriptive statistics, as well as criteria for sample inclusion, is detailed in Appendix B.6

Drawing from our theoretical framework, our analysis will focus on analyzing the differences in ARPK and capital-labor ratios between Black- and White-owned firms. To operationalize our analysis, we need to take a stand on what constitutes capital

6For readers who are more interested in the broader characteristics of this data set, Robb and Robinson (2014) provide a detailed breakdown of the characteristics of the data.
and labor in our data set. For capital, we utilize the sum of all non-cash assets on
the firm’s balance sheet, and include only firms reporting at least $1000 in non-cash
assets. For labor, a key issue arises because under half of all firms are non-employer
firms. Consequently, for the baseline analysis that we report in the main text, labor
is defined as the sum total of the number of workers hired by the firm, and the
number of owner-operators of the firm. We further report in Appendix C a sequence
of robustness checks where we vary the definition of labor.

3.2 Cross-Sectional Facts

For all our reported cross-sectional facts below, we pool our panel and run regressions
of the form

\[ \log y_{i,j,t} = \alpha + \delta \times I_{black} + X'_{i,t} \beta + \gamma_j + \theta_t + u_{it}, \]  

(5)

where \( y_{i,j,t} \) is the outcome variable of interest for a firm run by individual \( i \), in industry
\( j \), at year \( t \), \( \alpha \) is a common intercept term, \( X_{i,t} \) is a vector of individual specific
control variables, \( \gamma_j \) and \( \theta_t \) are industry and year fixed effects respectively, and \( u_{it} \) is
the error term. \( I \) is an indicator variable that evaluates to 1 if the individual is a
Black entrepreneur, and 0 otherwise; therefore, \( \delta \) is our effect of interest, capturing
whether Black-owned firms are statistically different from White-owned firms for the
specified outcome of interest.

3.2.1 Black entrepreneurs, relative to White entrepreneurs, operate firms
with lower capital intensities.

In Panel A of Table 1, we report regressions of the capital-labor ratio. Column
1 reports our headline estimate, where our regression is run without any control
variables besides year and industry fixed effects. As we can see, the average Black-
owned firm operates with 0.522 log-points lower capital-labor ratio. Viewed through
our framework, this provides suggestive evidence that Black entrepreneurs face tighter
credit constraints relative to White entrepreneurs.

An issue is that a multitude of unobserved factors might influence the borrow-
ing constraints of Black entrepreneurs, but which might not directly be related to
race-based financial discrimination. For instance, if Black entrepreneurs have lower
experience on average, due to other societal factors that impede human capital accumulation, then financial operators might be less willing to extend credit simply based on the riskiness and expected profitability of the firm.

To ensure the robustness of our results, we conduct a sequence of additional checks. In Column 2, we repeat our analysis including as control variables key characteristics of the primary owner, including length of prior relevant work experience, age, number of hours worked, percent of ownership, and gender. Our variables are chosen to control for factors associated with the productivity of the firm, which can affect our analysis if productivity is systematically correlated with race. The first two variables help address confounding effects coming through differential human capital accumulation across racial groups, an observation that is well known in the labor economics literature; the third variable helps to control for productivity if the number of hours worked is increasing in the productivity of the firm; while the fourth variable helps us to control for the degree to which the owner has sufficient “skin in the game”, which might affect the profitability of the firm. Finally, to the extent that race and gender are correlated in terms of selection into entrepreneurship, our last variable then helps control for the potential that firm profitability is associated with gender. We find that our results are robust to these controls, with the coefficient remarkably similar to our baseline.

Next, in Column 3, we repeat our estimation by additionally controlling for the personal wealth of the primary owner. Controlling for wealth could be important, given the well-documented racial wealth gap. For instance, if Black and White entrepreneurs faced identical collateral constraints, then Black-owned firms might operate with lower capital intensities because they have fewer assets as collateral. As we can see, such concerns are valid, with the magnitude of the coefficient falling by almost half. However, the estimate remains statistically significant at conventional levels, suggesting that the racial wealth gap is not the sole determinant of our headline finding.

An issue with the above analysis is that the wealth variable is only available for the year 2008 onwards. Consequently, the results in Column 3 are not comparable to that in Column 2, especially given the single-cohort nature of our data. Therefore, in Column 4, we repeat our analysis using the post-2007 sample without controlling for wealth. Interestingly, we find that the estimated coefficient is almost identical to that for the full sample.
Taken as a whole, we have presented stylized evidence that Black-owned firms operate with lower capital-intensity. Interpreted through our theoretical framework, this is suggestive that Black, relative to White, entrepreneurs face larger barriers in access to credit. We now turn towards providing evidence that suggests that Black entrepreneurs also simultaneously face substantial barriers with regards to demand.

3.2.2 Black entrepreneurs, relative to White entrepreneurs, operate firms with lower average returns to capital.

In Panel B Table 1, we report regressions of log ARPK. Our analysis is conducted similarly to that for the capital-labor ratio. In Column 5, we report regressions without any control variables besides industry and year fixed effect, and find that Black-owned firms operate with 0.373 lower log-points in ARPK relative to White-owned firms.

Our baseline result is striking. As we discussed in Section 2, a firm that is more financially-constrained would, holding all else constant, operate with higher ARPK. In the earlier subsection, we find stylized evidence that Black entrepreneurs face tighter credit constraints. Consequently, our finding here suggests that the demand-side discrimination that Black entrepreneurs face is sizable, to the point that it is able to “flip the sign” on our coefficient.

Similar to the earlier analysis, the lack of control variables imply that confounding factors that lower the productivity of Black entrepreneurs will also affect our inference. Since lower productivity also acts to lower the markups firms can charge, our baseline estimate is not directly indicative that Black entrepreneurs face discrimination in demand. To ensure the robustness of our results, we therefore control for the same set of covariates as in the exercise in Column 2 of Table 1. We find that our results are robust, with $\delta$ continuing to be statistically significant and negative (Column 6).

We next turn to examining whether wealth is also a determinant of these differences in ARPK. In Column 7, we include wealth as an additional control, and we find that the coefficient is smaller relative to our analysis without wealth. That said, as we already mentioned, part of these differences could be attributed to a change in the sample. Consequently, in Column 8, we reanalyze the results of Column 2 keeping only to the post-2007 sample. Here, we find that controlling for wealth does not change the estimate in a statistically significant sense.
3.3 Further Evidence of Demand Discrimination

A natural issue with our interpretation of demand-side discrimination so far is that there might be market segmentation for goods and services between Black and White consumers. Specifically, if Black and White businesses are producing goods that are specific to the preferences of their relevant racial groups (perhaps due to familiarity), then part of our estimated differences might arise entirely due to the different income levels of Black and White consumers. Because our simple framework cannot directly identify the sources of demand-side differences, it is reasonable to believe that our estimated differences in ARPK is driven by market segmentation, specifically, that Black consumers simply have lower disposable income.

To address this issue, we turn towards a richer identification strategy, where we exploit the idea that pure demand-side discrimination should generate a larger profitability gap in industries where goods are relatively more homogeneous. Put simply, to the extent that Black businesses face discrimination from White customers, Black individuals operating in markets with homogeneous goods would face relatively lower demand than those in markets with less homogeneous goods, since a fraction of their Black consumer base is “lost” to White businesses. In contrast, business owners in markets with less homogeneous goods are less affected by racial discrimination directly, since they have a captured consumer base.

To test our hypothesis, we run the following regression as given by equation 6. This equation is similar to our previous specifications, with the exception that we also allow for an interaction term between the Black indicator function and an indicator function that evaluates to 1 when the sector the business is in produces a homogeneous good; correspondingly, our estimand of interest is $\nu$. For our purposes, we classify any firms that operate in the construction or manufacturing sector as producing a relatively homogeneous good, whereas firms operating in services and retail trade as producing a relatively less homogeneous. While admittedly crude, we believe our classification is reasonable and sufficient for our qualitative analysis (as an example, a house built by a Black-owned construction firm should not be objectively different from that of a White-owned construction firm, holding all else constant, whereas a Black-owned salon would presumably be better equipped to cater towards Black consumers given different fashion preferences or requirements). Therefore, our hypothesis, if true, would imply that $\nu < 0$, that is, Black firms in more homogeneous industries face
lower returns to capital.

\[ \log y_{i,j,t} = \alpha + \delta \times I_{\text{black}} + \nu \times I_{\text{black}} \times I_{\text{homog}} + X'_{i,t} \beta + \gamma_j + \theta_t + u_{it}, \]

(6)

We report our results in Panel B of Table 2, where Columns 5 through 8 reports regression specifications identical to that in Section 3.2. As we can see, regardless of control variables or sample subsets, the coefficient \( \nu \) is always statistically significant and negative, indicating that the returns to capital is lower for Black businesses operating in industries where the output good is relatively more homogeneous.

As a placebo test of our identification strategy (and classification choice), we re-estimate the regression above using the log capital-labor ratio as a dependent variable. Capital intensities in our theoretical framework do not depend on consumer preferences, since the technology choice is a result of the relative scarcity of inputs. As such, to the extent that our strategy is valid, we should detect no differences for Black individuals operating in industries with relatively greater homogeneity of output.

We report our results in Panel A of Table 2, where Columns 1 to 4 are ordered in the same way as Columns 5 to 8 of Panel B respectively. As we can see, in all specifications, Black individuals running businesses in industries with relatively more homogeneous outputs do not operate with capital intensities that are different from that of firms operating in industries with less homogeneous outputs.

Taken as a whole, we have presented evidence that Black-owned firms operate with lower ARPK, that when interpreted through our framework, implies that Black entrepreneurs face a lower demand relative to White entrepreneurs solely on the basis of race. Crucially, we argue that in light of our evidence regarding credit discrimination, this finding is suggestive that demand-side discrimination is substantial and of first-order relevance.

4 Racial Discrimination in Entrepreneurship — Time-Series Facts

We now conduct additional analyses using the time-series variation in our data to further support our point. Our analysis draws on insights from the macroeconomics
literature, arguing that credit constraints do not generate persistent differences across firms since firms can accumulate liquidity to the point that credit constraints are no longer binding (e.g., Moll (2014)). In our context, this implies that the differences in capital-labor ratio should fade out over time as Black entrepreneurs accumulate wealth.

In contrast, demand-side differences, especially in the short- to medium-term, are probably relatively stable. In other words, while Black entrepreneurs could in theory save out of their borrowing constraints, they will not be able to address demand-side discrimination independently. Consequently, differences driven by demand-discrimination, like our measure of ARPK, should persist over time.

To summarize then, our hypothesis is that the differences in capital-labor ratio that we document should decrease over time, whereas the differences in ARPK should be relatively stable. To test this, we exploit the panel structure of our data, and run regressions of the form

$$\log y_{i,j,t} = \alpha + \delta \times I_{black} + \zeta_t \times I_{black} + \gamma_j + \theta_t + u_{i,t},$$  

(7)

where the regression specification is similar to equation 5, but allowing for racial effects (as captured by $\zeta_t$) to also vary over time.

4.1 Capital Intensity Differences are Transient

Our baseline specification includes the control variables mentioned in the earlier section without accounting for wealth, due to our sample limitations. We report our results in Figure 1 in the form of predictive margins, specifically, computing the expected log capital-labor ratio for Black and White firms beginning in 2005 through to 2011.

Our analysis unveils two findings that we see as consistent with financial discrimination. Looking to the first half of the sample up to year 2008, we see a rapid convergence in the capital-labor ratio, exactly as we hypothesized. In other words, Black entrepreneurs, while facing tighter credit constraints, do accumulate sufficient liquidity to self-finance their firms over time. Notably, this finding is consistent with recent research by Kim et al. (2021) using detailed census data on the population of private businesses.

However, looking to the second half of the sample, we see a sudden divergence in
the level of the capital-labor ratio, which then persists toward the end of the sample. As is well known, the year 2008 is concurrent with a sharp financial crisis, with credit supply substantially restricted. Our finding suggests that in the wake of the Great Recession, credit was disproportionately rationed from Black-owned firms, leading to a divergence in the capital-labor ratio. This finding is consistent with our hypothesis that Black entrepreneurs face a larger barrier in accessing credit.

### 4.2 ARPK Differences are Persistent

Our baseline specification is identical to that in Section 4.1, and we report our results in Figure 2 in the form of predictive margins.

Our analysis unveils findings that we see as consistent with both demand and financial discrimination. First, looking to the broader time series, we see that the differences in ARPK is generally prevalent across the entire sample. This matches our hypothesis that demand-side discrimination generates persistent differences in ARPK, since Black entrepreneurs cannot unilaterally address this issue.

On the other hand, we do see suggestive evidence for convergence post-2008. That said, we argue that this is reflective of the tightening borrowing constraints that we already documented in Section 4.1. In other words, the convergence in ARPK here is driven by a reduction in the amount of capital available to Black-owned firms, rather than a sudden change in demand-side factors after the Great Recession.

To further buttress our point, we conduct an additional analysis involving the total revenue factor productivity (TFPR) of each firm. Like ARPK, TFPR is positively correlated with firm markups, and thus informative of demand-side discrimination. However, unlike ARPK, TFPR is less correlated with financial constraints, given that it measures revenue productivity over all factors. Consequently, this measure would be less affected by the increasing cost of capital for Black entrepreneurs post-2008.

A disadvantage of using TFPR is the need to assume a parametric form for the production function, which is why we have restricted our analyses so far to only ARPK. Regardless, we follow the literature (e.g., Hsieh and Klenow (2009)) by assuming that firms operate a Cobb-Douglas production function with a capital share of 1/3. TFPR is then simply the ratio of revenue to a geometric average of capital and labor inputs. We then perform similar regression analyses to that for ARPK. Our results are reported in Figure 3, which appear to corroborate our claim: TFPR is persis-
tently lower across time and does not converge, indicating persistence in demand-side discrimination.

4.3 Implications for the Racial Wealth Gap

We now close out this section returning to our primary motivation in the introduction. As we discussed, a key policy initiative in closing the racial wealth gap has been to address discrimination in credit markets with respect to small business lending. That said, because credit constraints do not have a persistent effect on firm outcomes, given the ability to accumulate liquidity, the racial wealth gap would not be a persistent fact over generations if credit discrimination was the only barrier. In contrast, persistent demand-side discrimination would in fact be a permanent barrier to wealth accumulation, since it effectively permanently reduces the profitability of Black-owned firms. Importantly, we argue that our empirical analysis in this section sheds further light on these two channels, and emphasizes the importance of the latter.

4.4 Alternative Explanations

Taken at face value, our key stylized facts, both in the cross-section and time-series, primarily establish that demand-side differences dominate credit-supply differences. Moreover, we interpret these differences as arising from race-based discrimination, having argued that these differences appear to survive a battery of control variables. In Appendix D, we further examine alternative plausible explanations for our findings, namely that (i) the demand-side differences are driven by negative selection of Black individuals into necessity entrepreneurship due to labor market frictions, (ii) the demand-side differences are driven by credit-constraints alone, and (iii) the credit-side differences are driven by labor market segmentation, where Black firms face a lower labor cost. In general, we find that these hypotheses, while plausible, do not appear to be reflected in the data.

5 Conclusion

We developed a theoretical framework to connect the joint distribution of firm-level returns-to-capital and capital-intensity to demand- and supply- side constraints faced
by firms. We then provide evidence that, when viewed through our framework, suggests that Black entrepreneurs face discrimination on both credit access (supply) and on customer demand. We further argue that the demand-side discrimination is more substantial, and propose that this is a potential source of the persistent racial wealth gap. Due to data limitations, we do not proceed to quantify the economic importance of this source, but instead leave this question for future research.

6 Figures and Tables

Table 1: Baseline results

This table reports an OLS regression of a dependent variable on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White. Each column reports the OLS result associated with a set of control variables or sample subset as described in the main text. Panel A (Columns 1 to 4) reports results associated with the log capital-labor ratio, and Panel B (Columns 5 to 8) reports results associated with log ARPK. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: log k</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>δ</td>
<td>-0.522</td>
<td>-0.497</td>
<td>-0.280</td>
<td>-0.470</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.084)</td>
<td>(0.086)</td>
<td>(0.105)</td>
<td>(0.110)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel B: log ARPK</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>δ</td>
<td>-0.373</td>
<td>-0.427</td>
<td>-0.389</td>
<td>-0.399</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>(0.092)</td>
<td>(0.118)</td>
<td>(0.119)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>8590</td>
<td>8545</td>
<td>4394</td>
<td>4450</td>
<td>8631</td>
<td>8586</td>
<td>4427</td>
<td>4483</td>
</tr>
<tr>
<td>R²</td>
<td>0.111</td>
<td>0.143</td>
<td>0.187</td>
<td>0.145</td>
<td>0.083</td>
<td>0.158</td>
<td>0.175</td>
<td>0.173</td>
</tr>
</tbody>
</table>
Table 2: Extended results

This table reports our estimation results per equation 6, where the coefficient of interest is \( \nu \). Panel A reports results associated with the log capital-labor ratio, and Panel B reports results associated with log ARPK. Each column reports the OLS result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

<table>
<thead>
<tr>
<th></th>
<th>Panel A: log ( \frac{k}{l} )</th>
<th>Panel B: log ARPK</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \delta )</td>
<td>-0.534 (0.091)</td>
<td>-0.298 (0.101)</td>
</tr>
<tr>
<td></td>
<td>-0.525 (0.092)</td>
<td>-0.369 (0.096)</td>
</tr>
<tr>
<td></td>
<td>-0.264 (0.116)</td>
<td>-0.285 (0.123)</td>
</tr>
<tr>
<td></td>
<td>-0.482 (0.121)</td>
<td>-0.301 (0.125)</td>
</tr>
<tr>
<td>( \nu )</td>
<td>0.095 (0.239)</td>
<td>-0.611 (0.309)</td>
</tr>
<tr>
<td></td>
<td>0.230 (0.246)</td>
<td>-0.487 (0.296)</td>
</tr>
<tr>
<td></td>
<td>-0.106 (0.264)</td>
<td>-0.686 (0.338)</td>
</tr>
<tr>
<td></td>
<td>0.086 (0.269)</td>
<td>-0.669 (0.338)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>8,590</th>
<th>8,545</th>
<th>4,394</th>
<th>4,450</th>
<th>8,631</th>
<th>8,586</th>
<th>4,427</th>
<th>4,483</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R^2 )</td>
<td>0.111</td>
<td>0.143</td>
<td>0.187</td>
<td>0.145</td>
<td>0.0838</td>
<td>0.158</td>
<td>0.176</td>
<td>0.174</td>
</tr>
</tbody>
</table>

This figure plots the expected log capital-labor ratio over time for Black-owned and White-owned firms. The predictive margins come from the regression specification as in Equation 7.

Figure 1: Average log capital-labor ratio over time.
This figure plots the expected log ARPK over time for Black-owned and White-owned firms. The predictive margins come from the regression specification as in Equation 7.

![Figure 2: Average log ARPK over time.](image)

**Table 3: Cross-section Results with SSBF03**

This table reports an OLS regression of a dependent variable on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White. Each column reports the OLS result associated with a set of control variables or sample subset as described in the main text. Panel A (Columns 1 to 3) reports results associated with the log capital-labor ratio, and Panel B (Columns 4 to 6) reports results associated with log ARPK. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: log (\frac{K}{L})</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\delta)</td>
<td>-0.321</td>
<td>-0.173</td>
<td>-0.167</td>
<td>-0.538</td>
<td>-0.407</td>
<td>-0.408</td>
</tr>
<tr>
<td></td>
<td>(0.187)</td>
<td>(0.190)</td>
<td>(0.189)</td>
<td>(0.232)</td>
<td>(0.220)</td>
<td>(0.230)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>3162</td>
<td>3144</td>
<td>3144</td>
<td>3138</td>
<td>3120</td>
<td>3120</td>
</tr>
<tr>
<td><strong>(R^2)</strong></td>
<td>0.063</td>
<td>0.089</td>
<td>0.096</td>
<td>0.019</td>
<td>0.053</td>
<td>0.053</td>
</tr>
</tbody>
</table>

Note: \(K \geq 1,000\): Net book value of any buildings and equipment or any other depreciable, depletable or intangible assets + Net Book value of land + Inventories

\(L\): total employees + owner
Table 4: Cross-section Results with SSBF03 – Robustness

This table reports an OLS regression of a dependent variable on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White. Each column reports the OLS result associated with a set of control variables or sample subset as described in the main text. Panel A (Columns 1 to 3) reports results associated with the log capital-labor ratio, and Panel B (Columns 4 to 6) reports results associated with log ARPK. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

<table>
<thead>
<tr>
<th></th>
<th>Panel A: log $\frac{k}{l}$</th>
<th>Panel B: log ARPK</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta$</td>
<td>0.331</td>
<td>0.1590</td>
</tr>
<tr>
<td></td>
<td>(0.217)</td>
<td>(0.219)</td>
</tr>
<tr>
<td>Observations</td>
<td>3162</td>
<td>3144</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.061</td>
<td>0.085</td>
</tr>
</tbody>
</table>

Note: $K | K \geq$ 1,000: Net book value of any buildings and equipment or any other depreciable, depletable or intangible assets + Net Book value of land + Inventories + Accounts receivable and trade notes.

$L$: total employees + owner

Table 5: Homogeneous goods effect: Cross-section Results with SSBF03

This table reports an OLS regression of a dependent variable on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White. Each column reports the OLS result associated with a set of control variables or sample subset as described in the main text. Panel A (Columns 1 to 3) reports results associated with the log capital-labor ratio, and Panel B (Columns 4 to 6) reports results associated with log ARPK. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

<table>
<thead>
<tr>
<th></th>
<th>Panel A: log $\frac{k}{l}$</th>
<th>Panel B: log ARPK</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta$</td>
<td>-0.305</td>
<td>-0.156</td>
</tr>
<tr>
<td></td>
<td>(0.194)</td>
<td>(0.195)</td>
</tr>
<tr>
<td>$\nu$</td>
<td>-0.281</td>
<td>-0.265</td>
</tr>
<tr>
<td></td>
<td>(0.711)</td>
<td>(0.837)</td>
</tr>
<tr>
<td>Observations</td>
<td>3162</td>
<td>3144</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.063</td>
<td>0.089</td>
</tr>
</tbody>
</table>

Note: $K | K \geq$ 1,000: Net book value of any buildings and equipment or any other depreciable, depletable or intangible assets + Net Book value of land + Inventories
\( L : \text{total employees + owner} \)

**Table 6:** Homogeneous goods effect: Cross-section Results with SSBF03 – Robustness

This table reports an OLS regression of a dependent variable on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White. Each column reports the OLS result associated with a set of control variables or sample subset as described in the main text. Panel A (Columns 1 to 3) reports results associated with the log capital-labor ratio, and Panel B (Columns 4 to 6) reports results associated with log ARPK. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

<table>
<thead>
<tr>
<th></th>
<th>Panel A: log ( \frac{k}{l} )</th>
<th>Panel B: log ARPK</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \delta )</td>
<td>-0.323 (0.282)</td>
<td>-0.512 (0.248)</td>
</tr>
<tr>
<td>( \nu )</td>
<td>0.018 (0.611)</td>
<td>-0.292 (1.038)</td>
</tr>
<tr>
<td>Observations</td>
<td>2719 2707 2707</td>
<td>3138 3120 3120</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.055 0.089 0.080</td>
<td>0.017 0.045 0.046</td>
</tr>
</tbody>
</table>

Note: \( K|K \geq \$1,000 \): Net book value of any buildings and equipment or any other depreciable, depletable or intangible assets + Net Book value of land + Inventories + Accounts receivable and trade notes.

\( L : \text{total employees + owner} \)
References


Appendices

A Proofs and Derivations

Here, we will expand on the derivations and proofs that lead up to Proposition 1.

A.I Derivations of Equations 2 to 4

For equation 2, it is straightforward to see that the first-order condition to the firm’s profit-maximizing problem is,

\[ MRPK \equiv \frac{\partial p(y, d, \tau^d_y)}{\partial k} y = (1 + \tau^*_y) r, \]  

(8)

where the term \( \frac{\partial p(y, d, \tau^d_y)}{\partial k} y \) is by definition the marginal revenue product of capital.

To derive equation 3, note that MRPK can be rewritten as,

\[ \frac{\partial p(y, d, \tau^d_y)}{\partial k} y = \frac{\partial p}{\partial y} \frac{\partial y}{\partial k} y + \frac{\partial y}{\partial k} p \]  

(9)

\[ = \frac{\partial y}{\partial k} \left( \frac{\partial p}{\partial y} y + p \right). \]  

(10)

Next, keeping in mind that

\[ ARPK \equiv \frac{py}{k}, \]

the ratio of MRPK to ARPK is given by

\[ \frac{MRPK}{ARPK} = \frac{\partial y/\partial k}{y/k} \left( \frac{\partial p/\partial y}{p/y} + 1 \right) \]  

(11)

where the term \( \frac{\partial y/\partial k}{y/k} \) is the output elasticity with respect to capital, which we have defined as

\[ \frac{\partial y/\partial k}{y/k} \equiv \epsilon_k. \]
and the term $\frac{\partial p/\partial y}{p/y}$ is the inverse of the price elasticity. Moreover, the price elasticity is related to the markup $\mu$ through the equation,

$$\frac{\partial p/\partial y}{p/y} = -\frac{\mu}{1 + \mu}.$$  

Substituting the markup formula back into the equation for the ratio of MRPK to ARPK gives us

$$ARPK = \frac{1}{\epsilon_k} (1 + \mu) MRPK.$$

Taking logs, we obtain equation 3 as in the main text.

For equation 4, we first note that a similar expression for the marginal product of labor can be obtained,

$$\frac{\partial p(y, d, \tau_g^d)y}{\partial l} = \frac{\partial y}{\partial l} \left( \frac{\partial p}{\partial y} + p \right) = w$$  \hspace{1cm} (12)

Next, by dividing equation 2 by 12 (and with slight abuse of notation), we obtain

$$\frac{\partial l/\partial k}{l/k} = (1 + \tau_g^r) \frac{r}{w}.$$  \hspace{1cm} (13)

where the term $\frac{\partial l/\partial k}{l/k}$ is simply the elasticity of substitution at some given $y$, which we defined in the main text as

$$\frac{\partial l/\partial k}{l/k} \equiv \epsilon_{k,l}.$$

Taking logs and with a slight rearrangement of terms gives us equation 4.

A.II Proof of Lemma 1

To prove this, we simply need to invoke our assumption that physical production is CES, which implies that the capital-labor ratio is only a function of $r$, $w$, and $\tau_g^r$. In turn, this implies that $\epsilon_{k,l}$ is also trivially a function of $r$, $w$, and $\tau_g^r$. Moreover, with
the CES production assumption, we can derive the following expression,

\[ \epsilon_k = \alpha \left( \frac{y}{k} \right)^{\frac{\eta-1}{\eta}} - 1 \]

where \( \alpha \) and \( \eta \) are the capital-intensity and elasticity of substitution parameters of the CES function respectively. But as we have already derived, the capital-labor ratio depends only on \( r, w, \) and \( \tau_e \); and consequently, \( \epsilon_k \) also depends only on \( r, w, \) and \( \tau_e \). Moreover, increases in \( \tau_e \) leads to a decrease in the capital-labor ratio, which in turn leads to a decrease in \( \epsilon_k \).

A.III Proof of Proposition 1

Note that with Lemma 1 in hand, the result on the capital-labor ratio naturally follows through; in particular, because the markup term does not enter into the equation for the capital-labor ratio, this object is not affected by markups. A similar direct result applies to the ARPK result, except that we now see that markups also appear in the formula.

B Data Source and Summary Statistics

B.I Survey Inclusion

As discussed in the main text, the universe of firms considered for survey inclusion in the KFS was all newly registered firms in 2004 from the Dun and Bradstreet database. However, given that the focus of the KFS is on new entrepreneurs, this universe is too broad, capturing a wide range of firms from newly registered subsidiaries to established firms spun off from family inheritances. Therefore, for actual inclusion into the survey, a firm must then satisfy at least one of the following conditions:

1. The business was started as independent business, or by the purchase of an existing business, or by the purchase of a franchise in the 2004 calendar year.

2. The business was \textit{not} started as a branch or a subsidiary owned by an existing
business, that was inherited, or that was created as a not-for-profit organization in the 2004 calendar year.

3. The business had a valid business legal status (sole proprietorship, limited liability company, subchapter S corporation, C-corporation, general partnership, or limited partnership) in 2004.

4. The business reported at least one of the following activities:

   (a) Acquired employer identification number during the 2004 calendar year

   (b) Organized as sole proprietorships, reporting that 2004 was the first year they used Schedule C or Schedule C-EZ to report business income on a personal income tax return

   (c) Reported that 2004 was the first year they made state unemployment insurance payments

   (d) Reported that 2004 was the first year they made federal insurance contribution act payments

All firms that satisfy at least one of these conditions then make up the sample population of the KFS.

B.II Descriptive Statistics and Variable Construction

For the purposes of our paper, we focus on the revenue, non-cash assets, and employment of the firm, as well as the race of the primary owner. As we discussed in the main text, we focus our analysis on firms that report at least $1000 in non-cash assets.

B.II.1 Variable Construction

Capital. The KFS provides the researcher the balance sheet of the firm, and it provides a breakdown of the type of capital asset that the firm owns. However, as in most standard models, we consider only a single generic capital asset of interest. As such, in order render the results comparable, we construct a representative single
asset, real capital stock, $K_{i,t}$, using the nominal value of capital assets as follows:

$$K_{i,t} = \sum_s \frac{K_{i,s,t}}{P_{s,t}},$$

where $P_{s,t}$ is the relative price of each capital type $s$ and vintage $t$. Subscript $i$ indexes the firm. The relative prices are taken from the BEA. For the aggregated capital stock, we consider the firm’s holdings of equipment or machinery, vehicles, land and buildings and structures, product inventories, and other properties. The value of product inventories are deflated using the GDP deflator.

**Revenue.** Revenue is taken directly from the survey, but deflated using the GDP deflator.

### B.II.2 Summary statistics

We report our summary statistics in Table 6 below.

**Table 7: Summary Statistics**

This table reports key summary statistics used in our analysis. The sample only includes business owners that identify as White or Black. White business owners account for about 94% of the sample. All dollar amount values are computed in 2009 dollars and rounded to the nearest whole dollar.

<table>
<thead>
<tr>
<th>Percentile</th>
<th>Revenue ($)</th>
<th>Non-cash assets ($)</th>
<th>Employment (#)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>White</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>28,477</td>
<td>12,619</td>
<td>0</td>
</tr>
<tr>
<td>50</td>
<td>108,713</td>
<td>46,710</td>
<td>1</td>
</tr>
<tr>
<td>75</td>
<td>395,155</td>
<td>170,979</td>
<td>4</td>
</tr>
<tr>
<td><strong>Black</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>9679</td>
<td>6,500</td>
<td>0</td>
</tr>
<tr>
<td>50</td>
<td>31,941</td>
<td>24,590</td>
<td>1</td>
</tr>
<tr>
<td>75</td>
<td>139,934</td>
<td>86,999</td>
<td>3</td>
</tr>
</tbody>
</table>

### C Robustness Checks

An important concern with our empirical analysis is the definition of labor, since almost half of KFS respondents are non-employer firms. In our baseline analysis, we define labor as the sum total of all employees and owner-operators. In this section, we explore the sensitivity of our analysis by considering alternative definitions of labor,
as well as a restriction of our analysis to employer firms only. We also investigate the sensitivity of our results regarding capital-intensity differences when we replace the capital-labor ratio with the capital-wage bill ratio.

C.I Capital-Labor Ratio Results

C.I.1 Full Time Workers only

In this specification, we define labor as the sum total of full time workers and owner-operators.

Table 8: Capital-labor ratio

This table reports an OLS regression of the log capital-labor ratio on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White. Each column reports the OLS result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>δ</td>
<td>-0.470</td>
<td>-0.456</td>
<td>-0.227</td>
<td>-0.439</td>
</tr>
<tr>
<td></td>
<td>(0.084)</td>
<td>(0.087)</td>
<td>(0.106)</td>
<td>(0.110)</td>
</tr>
<tr>
<td>Observations</td>
<td>8585</td>
<td>8540</td>
<td>4391</td>
<td>4447</td>
</tr>
<tr>
<td>R²</td>
<td>0.114</td>
<td>0.151</td>
<td>0.198</td>
<td>0.150</td>
</tr>
</tbody>
</table>

C.I.2 Employer firms only

In this specification, we define labor as the sum total of workers and owner-operators as in the main text, but restrict our analysis to only employer firms.

Table 9: Capital-labor ratio

This table reports an OLS regression of the log capital-labor ratio on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White. Each column reports the OLS result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

<table>
<thead>
<tr>
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<th>(1)</th>
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<tbody>
<tr>
<td>δ</td>
<td>-0.692</td>
<td>-0.666</td>
<td>-0.459</td>
<td>-0.655</td>
</tr>
<tr>
<td></td>
<td>(0.105)</td>
<td>(0.106)</td>
<td>(0.128)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>Observations</td>
<td>5037</td>
<td>5009</td>
<td>2461</td>
<td>2511</td>
</tr>
<tr>
<td>R²</td>
<td>0.147</td>
<td>0.180</td>
<td>0.223</td>
<td>0.174</td>
</tr>
</tbody>
</table>
C.I.3 Employer firms and full-time workers only

In this specification, we define labor as the sum total of full-time workers and owner-operators, but restrict our analysis to only employer firms.

Table 10: Capital-labor ratio

This table reports an OLS regression of the log capital-labor ratio on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White. Each column reports the OLS result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

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<tbody>
<tr>
<td>δ</td>
<td>-0.628</td>
<td>-0.619</td>
<td>-0.431</td>
<td>-0.628</td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td>(0.109)</td>
<td>(0.134)</td>
<td>(0.140)</td>
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<tr>
<td>Observations</td>
<td>5032</td>
<td>5004</td>
<td>2488</td>
<td>2508</td>
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<tr>
<td>$R^2$</td>
<td>0.149</td>
<td>0.171</td>
<td>0.200</td>
<td>0.153</td>
</tr>
</tbody>
</table>

C.II ARPK Results

C.II.1 Employer firms only

Table 11: ARPK

This table reports an OLS regression of log ARPK on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White. Each column reports the OLS result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

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<td>δ</td>
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<tr>
<td></td>
<td>(0.125)</td>
<td>(0.117)</td>
<td>(0.156)</td>
<td>(0.156)</td>
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<tr>
<td>Observations</td>
<td>5037</td>
<td>5009</td>
<td>2491</td>
<td>2511</td>
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<tr>
<td>$R^2$</td>
<td>0.076</td>
<td>0.119</td>
<td>0.132</td>
<td>0.132</td>
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</tbody>
</table>

C.III TFPR Results

We report our results using TFPR
This figure plots the expected log TFPR over time for Black-owned and White-owned firms. The predictive margins come from the regression specification as in Equation 7.

**Figure 3:** Average log TFPR over time.

D Exploring Alternative Explanations

We examine here some alternative hypotheses for our stylized facts.

**Selection Effects Due to Labor Market Frictions** There exists a vast literature in labor economics emphasizing the role of labor market frictions for Black entrepreneurs (e.g., Kawaguchi (2005)). Consequently, this might lead lower productivity Black individuals to pursue entrepreneurship out of necessity. Such negative selection can drive down revenue productivity (and thus ARPK), making it appear that Black entrepreneurs face demand-side discrimination.

However, we do not believe this to be a dominant force in the economy. Specifically, negative selection implies that Black entrepreneurs should be over-represented in the economy. In contrast, as we report in Table 6, our data shows that around 6% of startups are Black-owned, but Black individuals make up 13% of the civilian labor force (BLS (2020)). In other words, Black individuals are *under-represented* in the population of startups.
Credit Constraints as the Fundamental Barrier to Lower Demand  Recent research have emphasized the importance of growing intangible assets as such consumer demand or sweat equity as a source of firm growth (e.g., Moreira (2016); Argente et al. (2021); Bhandari and McGrattan (2021). If credit-constrained firms also face a comparative disadvantage in expanding their stock of intangible assets, then Black entrepreneurs might face lower revenue productivity simply from the presence of financial discrimination, rather than directly from demand-side discrimination.

That said, we argue that our evidence does not appear supportive of this hypothesis as a primary driver of our results. A corollary of this hypothesis is that convergence in financial conditions across both groups should in turn eliminate the differences in returns to capital. From Section 4, we know that this prediction is not borne out.

Segmented Labor Markets  Recent research has emphasized the possibility that Black-owned and White-owned firms face segmented labor markets due to homophily (e.g., Carrington and Troske (1998) and Giuliano et al. (2009)). In other words, firm owners might prefer to hire within their own racial groups, or workers might prefer to work for business owners of their own racial group. Given evidence that Black workers generally face a lower wage (e.g., Charles and Guryan (2008); Derenoncourt and Montialoux (2021)), this implies that holding all else constant, Black firms would engage in less capital-intensive production.

To investigate this, we re-conduct the same analysis in Section 3 but replacing the capital-labor ratio with the capital-wage bill ratio. From equation 4, we see that such an analysis in fact gives us a more direct measure of the difference in the cost of financing across the two groups. However, an issue arises that we do not observe equivalent wage payments to the owner, which is a substantial fraction of the true labor costs. Consequently, we conduct our analysis using two measures of labor cost. First, we simply use the labor expenses reported in the KFS as our measure of the wage bill. Second, we impute the total wage bill inclusive of the owner(s)’ own labor. Specifically, we divide the total wage bill by the number of employees to obtain a wage rate, and then multiply the wage rate by the total number of workers and owner-operators to obtain total imputed labor costs.

We report our results in Table 11, where Columns 1 and 2 report our results using the raw labor expense data. Column 1 does not include any control variables whereas
Column 2 includes the additional control variables as discussed earlier. Similarly, Columns 3 and 4 report our result using the imputed measure. Looking first to Columns 1 and 2, we see no statistical difference in the capital-wage bill for Black and White firms, which is potential evidence supporting the alternative hypothesis. That said, in Columns 3 and 4, we see that the Black firms operate with a lower capital-wage bill once we account for the owner(s)’ own labor supply, consistent with our hypothesis regarding tighter capital constraints for Black firms.

**Table 12: Capital-wage bill ratio**

This table reports an OLS regression of the log capital-wage bill ratio on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White. Each column reports the OLS result associated with a set of control variables as described in the text. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

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<th>(1)</th>
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</thead>
<tbody>
<tr>
<td>δ</td>
<td>0.074</td>
<td>0.092</td>
<td>-0.286</td>
<td>-0.314</td>
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<tr>
<td></td>
<td>(0.135)</td>
<td>(0.0127)</td>
<td>(0.057)</td>
<td>(0.058)</td>
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<tr>
<td>Observations</td>
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<td>4522</td>
<td>5451</td>
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<tr>
<td>$R^2$</td>
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<td>0.169</td>
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</tbody>
</table>