

Consumer Demand and Credit Supply as Barriers to Growth for Black-Owned Startups ^{*}

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Abstract

We formulate a theoretical framework showing that differences in returns-to-capital and capital intensity between groups of firms can identify, respectively, relative differences in consumer demand and credit constraints. Using micro-data on Black- and White-owned startups, we find, after accounting for confounding effects, robust evidence that Black-owned startups have lower returns-to-capital and lower capital intensity, implying that Black-owned startups face lower consumer demand and tighter credit constraints due to race alone. 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 tighter credit constraints are transitory, whereas lower demand is a persistent barrier to the growth of Black-owned firms.

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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 due to concerns about discrimination in credit supply. In contrast, while substantial research has uncovered consumer discrimination against racial minorities in narrow markets (e.g., cellphone retailers), studies on the role of consumer discrimination in the broader market as a barrier to successful Black entrepreneurship is sparse. In this paper, we study whether disparities in consumer demand and credit supply across Black- and White-owned startups is prevalent at an economy-wide level, whether one channel is more dominant than the other, and whether policies focusing on credit supply alone is sufficient to promote sustainable long-term Black entrepreneurship.

To answer our questions, we present a stylized theoretical framework where entrepreneurs decide on how much capital and labor to hire to maximize profits, subject to a demand function with non-constant price elasticities, and where Black entrepreneurs face consumer and credit discrimination. We derive two reduced-form equations that we show can be used to identify and isolate the degree of credit and consumer discrimination Black-owned firms face. Using firm-level panel data in the United States, and drawing inference from our theoretical model, we find evidence for tighter credit constraints and lower consumer demand on the basis of race alone. Crucially, we also find that Black entrepreneurs are able to overcome their initial credit constraint over time, but that consumer demand is persistently lower relative to White-owned firms. This implies that policies focused solely on raising credit supply for Black entrepreneurs can accelerate existing firms to their optimal unconstrained firm sizes, but is unlikely to address the fundamental barrier to success for Black entrepreneurship.

Identifying the existence of race-based barriers as a barrier to the growth and profitability of Black-owned firms is notoriously challenging, since direct evidence is sparse. Disentangling the demand and supply for credit is a challenge, making

¹For more details, go to www.whitehouse.gov.

identification of credit discrimination difficult. Likewise, identifying consumer discrimination typically requires the researcher to observe the actual prices charged by a firm relative to its marginal cost, but such data essentially does not exist. Our main methodological contribution is to emphasize how, using standard accounting data alone, one can identify (at the least, qualitatively) *both* credit and consumer discrimination. Therefore, we can in principle attribute the degree to which constraints in the supply of productive factors and consumer demand differentially affect the growth of Black-owned startups.

Our strategy relies on the assumption of firm-profit maximization, and that firms face downward sloping demand curves with non-constant price elasticities that are weakly increasing in prices. Within this framework, we show that the average differences in capital intensity (ratio of capital to labor) across Black- and White-owned firms can be used to identify the presence of credit discrimination. Similarly, average differences in the ratio of revenue to capital (the average revenue product of capital) can be used to identify the presence of consumer discrimination.

The essence of our framework rests on textbook derivations of firm production decisions under imperfect competition, and is similar to the argument made by the literature on capital misallocation (e.g., [Hsieh and Klenow \(2009\)](#)) and markup estimation (e.g., [Hall \(1988\)](#); [De Loecker, Eeckhout, and Unger \(2020\)](#)). To identify credit supply differences, we rely on the idea that for a given choice of output, a firm chooses a mix of capital and labor that is proportional to the relative prices of the two inputs. If capital is relatively more expensive, then a firm would operate with lower capital intensity. Using the insights of [Hsieh and Klenow \(2009\)](#), a discriminated firm would face a higher implicit capital cost and operate with a lower capital-labor ratio relative to an otherwise identical non-discriminated firm. Consequently, a simple test of the presence of credit discrimination is to compare the difference in average capital intensities between otherwise identical Black- and White-owned firms.

Identification of consumer demand differences follows similarly. Here, we rely on the fact that the average revenue product of capital (ARPK) is proportional to the markups firms charge. Given our assumptions, a firm facing higher consumer demand charges a higher markup; therefore, a discriminated firm charges a lower markup and reports a lower ARPK. Consequently, a simple test of the presence of consumer discrimination is to compare the difference in average ARPK between otherwise identical Black- and White-owned firms.

Taking these predictions to the data, we find that Black-owned firms operate with lower capital intensities and lower ARPK relative to White-owned firms, suggesting that both credit and consumer discrimination are present. Moreover, our results are robust to numerous alternative confounding explanations. The general threat to identification is the existence of omitted variables that are correlated with race, but which do not necessarily arise due to discrimination against Black-owned firms. While we always account for common confounding effects as discussed in the literature (e.g., Fairlie (2018)), we also incrementally consider as confounding effects: differential productivity, differential internal financial resources, market segmentation, differential labor costs, statistical discrimination due to differential riskiness, and negative selection. We find that accounting for these effects do not change our conclusion.

Our cross-sectional results implies the existence of both channels of discrimination, but do not inform us of the relative importance of each channel. Moreover, it does not reject the possibility that credit discrimination alone is the underlying source of the reduced demand Black-owned firms face, rather than consumer discrimination.

To shed light on these questions, we next exploit the time-series dimension of our data set. As is well known, if firm productivity is persistent, then a financially constrained firm will eventually grow out of their constraints through asset accumulation (e.g., Moll (2014)). A dominant credit constraint channel would imply slow rates of convergence; moreover, if the source of the ARPK differences are fundamentally due to credit constraints, then the gap in ARPK would also fade out over time.

We operationalize this insight in two ways. First, we simply estimate the gap in capital intensities and the gap in ARPK on a year-by-year basis, and track the changes over time. Hence we find that the gap in capital intensities rapidly converge over four years, whereas the gap in ARPK is stable over the same period of time. This suggests that credit supply differences are unlikely to be the driver of the gap in ARPK. Moreover, it suggests that despite the initial differential access to capital, Black entrepreneurs quickly accumulate enough assets to outgrow their disadvantage.

Second, we subset our sample of White-owned firms to a subset of firms reporting the same average initial capital intensity as the full sample of Black-owned firms, and a complement subset with higher capital intensities, and repeat our earlier year-by-year estimation of these gaps. Because Black- and White-owned firms from the first subset face identical initial financial conditions (through the lens of our framework), this analysis allows us to study whether credit discrimination differentially affects the

growth trajectory of Black firms. In this context, we find that the gap in capital intensities, relative to the complement set of White firms, narrow at the same rate for both Black- and White-owned firms. However, the gap in ARPK between Black- and White- owned firms is essentially identical for either subsets.

Taken in totality, this implies that race-based credit constraints alone do not differentially affect the ability of Black entrepreneurs to accumulate assets, whereas the differences in consumer demand are persistent and could permanently affect the profitability of Black-owned firms. In this light, we believe that policy tools based on increasing credit supply alone is unlikely to promote sustainable long-term Black entrepreneurship. Instead, keeping in mind that the demand differences we uncover is, at heart, a residual, further research on the direct source of these demand differences, and strategies to alleviate them, could be more important.

The rest of the paper is structured as follows. After the literature review, we present in Section 2 our theoretical framework. Following that, in Section 3, we present our main empirical results utilizing a cross-sectional analysis, and in Section 4, we present additional analyses to gauge the robustness of our results. In Section 5, we further present and discuss our time series results, and then we conclude our paper in Section 6.

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 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, Levine, and Giuliano \(2010\)](#) 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, Voelz, Wu, and Franco \(2018\)](#) on AirBnB). Our key identification strategy, emphasizing the study of firm behavior to detect consumer

discrimination, is similar to the empirical strategy adopted by [Gil and Marion \(2018\)](#) and [Cook, Jones, Logan, and Rosé \(2022\)](#). Overall, our conclusion regarding the prevalence of consumer discrimination is consistent with earlier findings. Importantly, we further document the persistent effects of consumer discrimination and its impact on firm 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 documenting financial discrimination against Black-owned firms (e.g., [Robb, Fairlie, and Robinson \(2009\)](#); [Chatterji and Seamans \(2012\)](#); [Bates and Robb \(2015\)](#); [Fairlie, Robb, and Robinson \(2020\)](#); [Kim, Lee, Brown, and Earle \(2021\)](#) and [Brown, Earle, Kim, Lee, and Wold \(2022\)](#)). 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 firm profit-maximizing framework, which allows us to uncover the presence of consumer discrimination. In turn, this allows us to emphasize the role of consumer demand, as opposed to financial constraints, in driving the persistence of a profitability gap between Black- and White-owned firms. In this dimension, our emphasis is similar to recent research highlighting the importance of group-based demand-side differences ([Hardy and Kagy \(2021\)](#)).

Third, our paper builds on, and adds to, the macroeconomics literature on factor misallocation, and in particular, misallocation driven by discrimination. We utilize the wedge accounting framework of [Hsieh and Klenow \(2009\)](#) to identify credit and consumer discrimination, but extend their model environment to allow for non-constant demand elasticities, which is crucial to identifying these two channels separately. In this context, we differ from the statistical approach adopted by the labor economics literature on studying disparities in outcomes across races in entrepreneurship (e.g., [Fairlie and Robb \(2007\)](#); [Fairlie \(2018\)](#); [Fairlie et al. \(2020\)](#)). On the empirical dimension, we also add to the small but growing literature in macroeconomics studying the impact of discrimination on aggregate outcomes (e.g., [Hsieh, Hurst, Jones, and Klenow \(2019\)](#); [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, Kim, Kuhn, and Schularick \(2021\)](#) and [Aliprantis, Carroll, and Young \(2021\)](#)) 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 attempt to uncover the source of this difference, arguing that the persistent return differences are driven by consumer demand differences. In contrast, our findings differ from the hypothesis put forth in [Boerma and Karabarounis \(2021\)](#), 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 analyses in Sections 3 to 5.

2.1 Model

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 $p(y_i, d_i, \tau_g^d)y_i$, 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 τ_g^d that all determine 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 τ_g^d , decreasing in y_i , and differentiable 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 τ_g^d 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. In this context, consumer discrimination refers to the case where $\tau_B^d - \tau_W^d < 0$; in other words, White-owned businesses can charge a higher price relative to Black-owned businesses for the exact same product.

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 $(1 + \tau_g^r)r$. 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 τ_g^r 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 τ_g^r ; in this context, financial discrimination refers to the case where $\tau_B^r - \tau_W^r > 0$. 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

$$\pi = p(y, d, \tau_g^d)y - (1 + \tau_g^r)rk - wl, \quad (1)$$

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,

$$MRPK = (1 + \tau_g^r)r. \quad (2)$$

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,

$$\log ARPK = \log MRPK + \log (1 + \mu (\tau_g^d, d; \tau_g^r)) - \log \epsilon_k. \quad (3)$$

Here, μ is the markup of the firm, which depends on the market structure (and hence the revenue generating function). Note that the markup formulation depends on both individual specific characteristics (d_i) that is independent of race, and race itself (τ_g^d). As such, for notational ease, we will denote markups as μ_{ig} going forward. Finally, ϵ_k is the elasticity of physical output with respect to capital, and arises only from the production side of the equation; specifically, increases in the relative capital intensity of the underlying production technology leads to an increase in ϵ_k .

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

$$\log \frac{k}{l} = \log \epsilon_{k,l} - \log r - \log (1 + \tau_g^r) + \log w. \quad (4)$$

Here, $\epsilon_{k,l}$ is an elasticity term capturing the marginal rate of technical substitution for a given level of output. Like ϵ_k , this arises entirely from the production side of the equation.²

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, ϵ_k and $\epsilon_{k,l}$, are functions of only r , w , and τ_g^r , and in particular, increasing in τ_g^r . 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 τ_g^r , that is, access to financing; (ii) differences in ARPK across groups are driven by both differences in τ_g^r and τ_g^d , that is, they depend on both access to financing and demand.*

²For instance, if the production function was Cobb-Douglas with capital exponent α , then $\epsilon_k = \alpha$, and $\epsilon_{k,l} = \frac{\alpha}{1-\alpha}$.

Moreover, holding all else constant, increases in τ_g^r (i.e., discrimination in access to financing) increases both ARPK and the capital-labor ratio, while decreases in τ_g^d (i.e., discrimination in consumer demand) reduces ARPK but has no effect on the capital-labor ratio.

2.2 Identifying Consumer and Credit Discrimination

Our identification strategy rests on simultaneously utilizing equations 3 and 4.

First, to identify the presence of credit discrimination, we look to equation 4. To set notation for the rest of the paper, we denote the difference in average implicit capital costs between Black and White firms by $\Delta\tau^r \equiv \log(1 + \tau_B^r) - \log(1 + \tau_W^r)$, and term this the capital cost wedge. If credit discrimination was present, then we would expect $\Delta\tau^r > 0$. Moreover, the capital cost wedge allows us to quantify the average relative difference in implicit financing costs between Black and White firms. Figure 1 provides a simple graphical representation of our identification strategy.

To operationalize this insight, note that because equation 4 is log-linear in its variables, we can identify the existence of credit discrimination by simply estimating the following equation using ordinary least squares:

$$\log\left(\frac{k}{l}\right)_{i,j,t} = \alpha + \delta \times \mathcal{I}_{black} + X'_{i,t}\beta + \gamma_j + \theta_t + u_{it}, \quad (5)$$

where $\left(\frac{k}{l}\right)_{i,j,t}$ is the capital-labor ratio for a firm run by individual i , in industry j , at year t , α is a common intercept term, $X_{i,t}$ is a vector of individual specific control variables, γ_j and θ_t are industry and year fixed effects respectively, and u_{it} is the error term. Finally, \mathcal{I} is an indicator variable that evaluates to 1 if the individual is a Black entrepreneur, and 0 otherwise. Consequently, δ is our estimate of interest, giving us an estimate for $\Delta\tau^r$.

Notably, an obvious issue with our estimation strategy is that any factor that correlates with racial differences, but has nothing to do with discrimination directly, would also show up in this wedge. For instance, since Black households have relatively less wealth due to the racial wealth gap, the decreased ability to self-finance might lead us to detect a positive wedge, and attribute this to racial discrimination. In general, we attempt to control for these effects by using a battery of control variables in the vector $X_{i,t}$. In the empirical section, we will address such confounding effects

in further detail.

Finally, another issue at hand is that heterogeneity in the production function itself might be a threat to our identification strategy (e.g., Foster, Haltiwanger, and Tuttle (2022)). Specifically, Black and White entrepreneurs might differentially sort into low (low $\epsilon_{k,l}$) and high (high $\epsilon_{k,l}$) capital-intensity technologies due to capital constraints generated by the racial wealth gap (as opposed to financial discrimination). In the extreme where individuals can completely bypass their capital constraints through sorting into low capital-intensity technologies, this would imply that $\tau_g^r = 0$ and all heterogeneity in the capital-labor ratio comes through $\epsilon_{k,l}$. Consequently, δ would pick up differences in $\epsilon_{k,l}$.³ However, this also implies that such a bias can be corrected (or reduced) when we control for wealth. We will discuss this effect in further detail later in the context of our empirical results.

Second, to identify consumer discrimination, we rely primarily on equation 3, where τ_g^d enters into the equation. Note that to the extent that consumer discrimination exists, differences in τ_g^d induces a wedge in markups between Black and White firms. Again to set notation for the rest of the paper, we denote this wedge in markups by $\Delta\mu \equiv \mathbb{E}[\log(1 + \mu_{ig})|g = B] - \mathbb{E}[\log(1 + \mu_{ig})|g = W]$, and term it the markup wedge. Here, keep in mind that the expectation operator is taken with respect to all the individuals within the same group. Moreover, if consumer discrimination was present, then we would expect $\Delta\mu < 0$. Our goal is therefore to identify the markup wedge. This strategy is similar to the capital cost wedge, except that we do not directly identify the differences in “demand” (i.e., τ_g^d).

A direct issue at hand is that we can see that τ_g^r is also a confounding variable. For instance, a Black firm facing both consumer and credit discrimination might report an ARPK that is identical to a White firm if both forces cancel out each other. That said, our framework provides a ready solution: The capital intensity of the firm is a direct proxy variable for the cost of capital. In this regards, we can simply estimate equation 3 while controlling for the firm’s capital intensity. Specifically, we estimate the following equation,

$$\log arpk_{i,j,t} = \alpha + \delta \times \mathcal{I}_{black} + \varsigma \log \left(\frac{k}{l} \right)_{i,j,t} + X'_{i,t} \beta + \gamma_j + \theta_t + u_{it}, \quad (6)$$

³Note that in the case where financial discrimination is the source of this endogenous sorting, an estimate of $\delta < 0$ continues to qualitatively detect financial discrimination, except that the interpretation is no longer strictly about implicit capital cost differences.

where the specification is identical to equation 5 except that our dependent variable of interest is now the ARPK of the firm, and we explicitly control for the capital-labor ratio. Based on our theory, this estimation framework would give us a consistent estimate of the markup wedge through δ .

Like with estimating credit discrimination, an issue here is that any factor that correlates with group differences, but has nothing to do with discrimination directly, would also show up as a markup wedge. In this context, the biggest concern is that long-running racial disparities in the education and labor markets might reduce the human capital of Black entrepreneurial firms. In other words, Black firms might simply have lower productivity relative to White firms that our controls in X_{it} cannot account for. Given our assumption on the demand function, this productivity difference would also generate the same markup wedge as consumer discrimination.

We briefly highlight here why we do not think that productivity differences are a substantial issue. In Figure 2 (left panel), we illustrate our identification argument, building in the assumption that productivity across groups are identical. As we can see, higher demand generates higher markups via higher prices, but marginal cost curves are identical by assumption. What about productivity differences? In Figure 2 (right panel), we now plot the pure effect of productivity differences, assuming identical demand (i.e., no consumer discrimination). In this context, higher productivity firms charge a higher markup, but also simultaneously charge lower prices due to lower marginal costs. Such a result appears potentially counterfactual given recent evidence that Black vendors tend to charge lower prices within narrowly defined markets (e.g., [Doleac and Stein \(2013\)](#); [Edelman and Luca \(2014\)](#); [Kakar et al. \(2018\)](#)). Regardless, in the empirical section, we will address such confounding effects in further detail.

While we argue that differences in physical productivity is unlikely to be a confounding effect, a parallel threat to our identification of consumer discrimination is that any confounding factors that reduces the pricing power of Black-owned firms would also give rise to a markup wedge. For instance, if human capital affects the ability to acquire customer capital rather than physical productivity (e.g., [Moreira \(2016\)](#)), our argument in the preceding paragraph would no longer hold. In this context, while we attempt to account for differential human capital in our empirical results, τ_g^d is at heart a residual, and we cannot account for the universe of confounding effects. We therefore acknowledge this shortcoming, and note that the term "consumer discrimination" is used in the context of the literature to imply an unex-

plained residual that is correlated with race (e.g., [Borjas and Bronars \(1989\)](#); [Bento and Hwang \(2021\)](#)).⁴

Importantly, our results clarify two key issues that might influence inference on financial discrimination for current research. On the one end, recent papers in the finance literature (e.g., [Fairlie et al. \(2020\)](#); [Kim et al. \(2021\)](#)) identify financial discrimination by essentially estimating the average difference in capital stock between Black and White firms. Our theoretical model shows that a Black firm would be smaller than a White firm even if they did not face credit discrimination, so long as they also faced consumer discrimination. Instead, a distortion of the factor mix (i.e., capital-labor ratio) is key for identifying credit discrimination.

On the other end, recent papers in the macroeconomics literature (e.g., [Morazoni and Sy \(2022\)](#); [Bento and Hwang \(2021\)](#)) emphasize differences in ARPK as an identification strategy for detecting financial discrimination. We show that this identification is valid so long as markups do not vary across firms. However, if markups did vary across firms, consumer discrimination would confound the analysis.

In this light, we now turn towards our empirical section to assess the relative importance of consumer demand and credit supply as a source of discrimination for Black entrepreneurs.

3 Main Results

In this section, we introduce our data source and report our key empirical findings, namely, that Black entrepreneurs, through the lens of our framework, face discrimination in both credit supply and consumer demand. We further discuss the robustness of our empirical results in [Section 4](#).

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

⁴This issue is less likely of a problem for identifying credit discrimination, since the demand for credit is unlikely to be systematically correlated with human capital.

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-operator. Importantly, the latter variable is not typically available in most firm-level data. In this context, we encode all firms as Black-owned (White-owned) if the primary owner-operator of the firm self-reports as Black (White). Descriptive statistics, as well as criteria for sample inclusion, is detailed in Appendix C.⁵

Drawing from our theoretical framework, our analysis will focus on estimating 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 and labor in our data. 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 D a sequence of robustness checks where we vary the definition of labor.

Finally, for all our reported cross-sectional facts below, we pool our panel and run regressions of the form expressed in equations 5 and 6.

3.2 Baseline Cross-Sectional Facts

In this subsection, we focus on reporting our baseline results building on our theoretical model. In what follows, for the sake of exposition, we will also use the terms “capital intensities” and “returns to capital” as synonyms for “log capital-labor ratio” and “log ARPK”.

3.2.1 Black, relative to White entrepreneurs, face higher implicit financing costs.

In Panel A of Table 1, we report regressions using the log capital-labor ratio as the dependent variable. Column 1 reports our headline estimate, where our regression is run without any control variables besides year and industry fixed effects. Interpreting

⁵For 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.

the coefficient as an implicit capital cost wedge, we find that Black-owned firms face an average of around 52% higher cost of capital relative to White-owned firms.⁶ 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 borrowing constraints of Black entrepreneurs, but which might not directly be related to credit 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 the number of years of prior relevant work experience (in logs), education (categorized in three groups as below college degree, some college degree, and some advanced degree), age (in logs), number of hours worked (in logs), 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 three 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 fourth variable helps to control for productivity if the number of hours worked is increasing in the productivity of the firm; while the fifth 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.⁷ 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 en-

⁶As a concrete example, if the market interest rate was 4%, then the average Black firm would face an implied interest rate of 6.1%.

⁷Moreover, we choose these variables as controls since they are known to be strong correlates of business success, independent of race alone. See, for instance, the comprehensive review by Fairlie (2018).

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.

However, as the wealth variable is only available for the year 2008 onward, 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. We find that the estimated coefficient is very similar to that for the full sample when wealth is no longer controlled for, suggesting that there is indeed a role for wealth differences in explaining the differences in capital intensities across the two racial groups.

3.2.2 Black, relative to White entrepreneurs, face lower consumer demand.

In Panel B of Table 1, we report regressions using log ARPK as the dependent variable. Our analysis is conducted similarly to that for the capital-labor ratio, keeping in mind that the log capital-labor ratio is also always a control variable in all our specifications. In Column 5, we report regressions without any additional control variables besides industry and year fixed effect, and find a markup wedge of -68%. This suggests that Black entrepreneurs, holding all else constant, face relatively lower consumer demand, which we attribute in our context to consumer discrimination.

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 δ continuing to be statistically significant and negative (Column 6).

We next turn to examining whether wealth is also a determinant of the markup wedge. In Column 7, we include wealth as an additional control variable, and find that the coefficient is smaller relative to our baseline. However, since this decline could be attributed to a change in the sample, we reanalyze our results keeping only

to the post-2007 sample, without controlling for wealth. Here, we find that controlling for wealth does not change the estimate in a statistically significant sense (Column 8).

3.2.3 Does heterogeneity in production technologies confound our results?

Having presented our results in totality, we now briefly discuss why we do not think that heterogeneity in production technologies is a source of bias in our estimation strategy. Our argument rests on the fact that, while controlling for wealth appears to attenuate the estimate on the race dummy variable in the capital-labor ratio regression, it does not meaningfully affect the estimate for the ARPK regression.

To see this argument, notice that we can explicitly re-write equation 3 as

$$\log ARPK = -\log \frac{k}{l} + \log(1 + \mu_{ig}) - \log \epsilon_k + \log \epsilon_{k,l} + \log w. \quad (7)$$

In this context, selection bias due to heterogeneity in production technologies lead to omitted variable bias in estimating equation 6, since ϵ_k and $\epsilon_{k,l}$ are not explicitly accounted for. In other words, δ no longer simply picks up relative differences in $\log(1 + \mu_{ig})$, but also ϵ_k and $\epsilon_{k,l}$. That said, this implies that if such a selection effect were present, using additional variables that can control for the omitted variables should substantially change the resulting estimate.

This argument therefore implies a straightforward test. As we already saw, the inclusion of wealth as a control variable reduces the capital cost wedge between Black- and White- owned firms. However, this effect could arise due to two concurrent factors, namely that wealth is indeed controlling for the capital cost wedge as we hypothesize, or wealth is in fact controlling for selection into different technologies. To the extent that the former is the dominating effect, controlling for wealth in the ARPK regression would not attenuate the estimate of δ , since the capital cost wedge effect is already controlled for with the capital-labor ratio (i.e., τ_g^r does not appear in equation 7). In contrast, if the latter effect was dominant, then controlling for wealth would affect the estimate of δ , since an omitted variable is now partially accounted for. In this context, since δ does not materially change when we control for wealth in the ARPK regression, we do not think that selection into different production technologies is a meaningful source of bias.

4 Robustness Analysis of Main Results

In this section, we further address the robustness of our results. Specifically, we address three potentially important confounding effects. First, we ask whether statistical discrimination on the part of financial lenders could be the driver behind our findings regarding the differences in implicit financing costs. Second, we address whether unmeasured productivity differences could be driving the differences in markups. Finally, we also address whether market segmentation across racial groups, that is unrelated to taste-based discrimination, could be a driver of the differences in markups.

4.1 Can Statistical Discrimination Explain the Capital Cost Wedge?

While we attribute the gap in implicit financing cost to taste-based discrimination, a large literature does emphasize the role of statistical discrimination (e.g. [Blanchflower, Levine, and Zimmerman \(2003\)](#), [Cavalluzzo and Wolken \(2005\)](#), [Blanchard, Zhao, and Yinger \(2008\)](#), [Bates and Robb \(2016\)](#), [Bates, Bradford, and Jackson \(2018\)](#)). In other words, while we have shown that financing differences exist, we cannot reject the existence of underlying real factors that are correlated with race as the source of these observed differences, but not necessarily explicitly race-based. To address this concern, we now examine to what extent a key source of statistical discrimination, namely, risk differences at the firm level, might be the fundamental driver of the wedge in implicit financing costs.

4.1.1 Measuring Risk: Are Black Firms Riskier?

We proxy for the riskiness of firms using four measures. The first three measures are direct measures of credit risks as reported in the KFS, and computed by Dun and Bradstreet. The first measure comes from the firms' commercial credit score, as binned into 5 categories, with a bin of 1 indicating firms with the highest risk. The second two measures are computed by Dun and Bradstreet. *PAYDEX* score reports the timeliness of a company in repayment. A lower *PAYDEX* score implies a higher degree of delinquency in payment. The financial stress score probability (FSSP) reports the probability that a firm would enter into financial stress in the next twelve

months, with an emphasis on business failure. All measures are decreasing in risk.

However, because the first three measures are computed by an external agency, they might not be objective measures, or might confound lower profitability or higher failure likelihood (i.e., first moment effects) with risk (i.e., second moment effects). As such, they might not accurately capture economic risk. To address this, we also independently construct a measure of ex-post risk by computing a rolling standard deviation of returns on assets (e.g., [Faccio, Marchica, and Mura \(2016\)](#), [Morazzoni and Sy \(2022\)](#)). As is common to the economics literature, a larger volatility in return on assets is associated with increased riskiness. Our construction of returns on assets (ROA) follows [Morazzoni and Sy \(2022\)](#), who utilize the same dataset as our paper.

To investigate the relevance of these measures as proxies for risk, we first run a regression of the log capital-labor ratio on the aforementioned measures. To the extent that our theory matches up with these proxies, we should find that riskier firms operate with lower capital intensities. This intuition is borne out, as we report in [Table 2](#). As we can see, firms with lower subjective and objective measures of risk all operate with higher capital intensities.

To investigate the possibility of statistical discrimination, we first run a regression of the aforementioned risk measures on a dummy indicator for race. We report these results in [Table 3](#). In Panel A, we first estimate this correlation for our full sample. Reflecting our concerns, we do find that Black firms in general are riskier as measured both by subjective and objective measures. For instance, Black firms have lower credit score bins and report higher volatility on average. This finding is true even after we control for observable covariates and wealth, as in [Section 3](#).

We further study the validity of these four measures as measures of risk, and thus a good control for statistical discrimination. Here, we hypothesize that within narrowly defined groups of “higher quality” firms, race should now matter less as a correlate of these measures since statistical differences are now less prominent. In other words, higher quality firms should be more similar in terms of risk characteristics compared to the general population. Therefore, race should no longer be (or at least, substantially less) correlated with risk.

For this analysis, we consider two subsets of firms: One subset that includes only firms run by individuals with at least an advanced degree (Masters degree and above), and a separate subset of firms that were incorporated. The results are reported in [Panels B and C](#).

We find that from an objective measure (Column 10 to 12), Black owned firms are not any riskier than White owned firms, supporting our intuition that race should matter less within these subsets since observable statistical differences are narrowed. Surprisingly however, we find that Black firms continue to exhibit worse subjective risk measures (Columns 1 to 9).

These findings suggest that the Dun and Bradstreet risk measures are potentially confounding both first and second moment effects, capturing in part the lower return on asset anticipated for Black firms, rather than risk alone. To test this hypothesis, we simply run a regression of log ARPK on the four risk measures. Using standard economic theory, a riskier firm should exhibit higher expected returns, holding all else constant, given the associated risk premium. Indeed, we find this standard positive relationship between our objective measure and ARPK, as we report in Column 4 of Table 4. In contrast, for the Dun and Bradstreet measures, we find that “riskier” firms exhibit lower returns on average, suggesting that the aforementioned risk measures do not simply capture second moment effects alone.

Having established the potential relevance of statistical discrimination, and keeping in mind the caveats regarding the subjective measures of risk, we now turn to understanding the extent to which statistical discrimination changes our findings.

4.1.2 Does statistical discrimination account for all financing differences?

To examine the importance of statistical discrimination as a driver of our findings, we re-run our earlier baseline specifications, but now also including each of the four measures of risk as control variables. For comparability, we report results for our baseline without any other controls (Panel A), our specification with controls (Panel B), and our last specification that also includes wealth as a control (Panel C). Our results are reported in Table 5.

Column 1 report our baseline result from earlier, and in Columns 2 to 5, we report the same coefficient but controlling for each risk factor. We see that the inclusion of a risk control generally attenuates our estimate of the impact of race. For instance, for our estimates without control variables, this attenuation ranges from around 10% (vol ROA) to 50% (*PAYDEX*).

In Columns 6 and 7, we re-run our baseline specification using our advanced degree and incorporated firms subsets, but without explicitly controlling for the aforementioned risk variables. As we already showed, the *objective* riskiness of Black firms

within this group is similar to that of White firms. Consequently, we should expect that the differences in capital intensity should be lower within this group, relative to the full sample, since statistical discrimination should be less relevant for financing. This is indeed what we find. In Column 6, we see that race is essentially uncorrelated with capital intensity within the advanced degree subset, whereas for the incorporated subset, the coefficient is attenuated by approximately 40%.

Taken together, our results suggest that while statistical discrimination does appear to explain a substantial fraction of the wedge in implicit financing cost, it does not fully explain these differences, implying that differences based on race alone continue to play an important role. That said, we do find that obtaining an advanced degree does appear to fully mitigate these differences.

4.2 Can Productivity Differences Explain the Markup Wedge?

We next turn to addressing whether productivity is systematically different across the two racial groups, given the well documented gap in educational and labor market outcomes across Black and White individuals (Card and Krueger (1992), Neal and Johnson (1996), Heckman, Lyons, and Todd (2000), Bayer and Charles (2018)). Note that while we do control for standard covariates like education in our baseline specification, there is a possibility that such a crude control does not directly capture productivity. In particular, it has been well documented that Black and White individuals face starkly different education quality (e.g., Hanushek, Kain, and Rivkin (2009), Fryer (2011)). In other words, do Black firms perform worse simply because they have lower productivity on average?

We examine this by re-running our baseline regression specification for our Advanced Degree and S-Corp/LLC subsets. Our key intuition here is that the disparities in terms of education quality should be narrower as one ascends the education ladder. Likewise, since incorporation is typically done only within higher quality firms (e.g. Chen, Qi, and Schlagenhauf (2018), Barro and Wheaton (2020), Gregg (2020)), the disparities in firm productivity should also be narrower within this group, to the extent that any factual differences exist.

Our results are reported in Table 6. Like before, for comparability, we report results for our baseline without any other controls (Panel A), our specification with controls (Panel B), and our last specification that also includes wealth as a control

(Panel C). Here, we find that by and large, the difference in average markups between Black- and White-owned firms are similar or even larger than in the full sample. As such, we argue that productivity differences are unlikely to be a substantial determinant of the differences in markups.

4.3 Can Market Segmentation Explain the Markup Wedge?

A natural issue with our interpretation of consumer 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 markup differences, it is reasonable to believe that our estimated difference 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 consumer 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. A key assumption here is that Black consumers shopping in either markets have the same average income.

To test our hypothesis, we run the following regression as given by equation 8. 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 ν . 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.

$$\log y_{i,j,t} = \alpha + \delta \times \mathcal{I}_{black} + \nu \times \mathcal{I}_{black} \times \mathcal{I}_{homog} + X'_{i,t}\beta + \gamma_j + \theta_t + u_{it}, \quad (8)$$

We report our results in Panel B of Table 7, 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 ν 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 equation 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, if 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 7, 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.

4.4 Other Alternative Explanations

In Appendix E, we further examine alternative plausible explanations for our findings, namely that (i) the markup wedge is driven by negative selection of Black individuals into necessity entrepreneurship due to labor market frictions, and (ii) the capital cost wedge is 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 Which Matters More? Factor Supply or Customer Demand?

Our earlier section establishes the presence of both credit supply and customer demand discrimination. We now extend our empirical analysis to study the relative importance of these two channels in serving as a barrier towards equalizing entrepreneurial opportunity between Black and White business owners. We primarily argue in this section that there exists evidence that Black entrepreneurs are able to overcome their initial barriers with regards to financial constraints, but are not able to overcome the demand-side constraints. Consequently, we argue that customer demand discrimination appears to play a much larger role.

5.1 Empirical Strategy

Our empirical strategy borrows from insights drawn from the macroeconomics literature. Specifically, this literature argues 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 capital cost wedge should fade out over time as Black entrepreneurs accumulate sufficient wealth to negate the constraints on credit supply.

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 consumer discrimination independently. Consequently, the markup wedge should persist over time.

Taken together, we therefore hypothesize that over the life cycle of the firm, customer discrimination would matter more than credit discrimination. That said, the degree to which credit supply or customer demand is more important depends on the persistence of the capital cost wedge between Black- and White-owned firms; in particular, a relatively high rate of converge in capital intensities would imply that Black-owned firms can quickly “self-finance” out of their constraints, and thus mitigate the impacts of financial constraints.

To operationalize this intuition and test our hypothesis, we exploit the panel structure of our data, and run regressions of the form

$$\log y_{i,j,t} = \alpha + \zeta_t \times \mathcal{I}_{black} + X'_{i,t}\beta + \gamma_j + \theta_t + u_{i,t}, \quad (9)$$

where the regression specification is similar to equation 5, but allowing for racial effects (as captured by ζ_t) to also vary over time. By comparing ζ_t over time, we will be able to analyze the degree to which the capital wedge closes over time.

5.2 Main Results

5.2.1 Capital Intensity Differences are Transient

We first report our findings for the capital cost wedge. 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 3 in the form of predictive margins, computing the expected log capital-labor ratio for Black- and White-owned firms beginning in 2005 through to 2011.

Our analysis unveils two key findings. Looking to the first half of the sample up to year 2008, we see a rapid convergence in the capital-labor ratio (i.e., reduction in the capital cost wedge), 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. In general, this suggests that Black-owned firms do inherently have the ability overcome their financial constraints over time, and at a relatively fast rate.

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.

Broadly speaking, our analysis brings to light a key finding: The dynamics of capital accumulation for Black-owned firms are not impeded by credit supply constraints.

This implies that Black-owned firms are able to rapidly reach their optimal factor mix, and thus their initial disadvantage is not binding. Our finding mirrors recent research by Fairlie et al. (2020) using the same KFS data but with a key difference. Unlike their paper, we emphasize a rapid reduction in the *capital cost wedge*, whereas the authors emphasize that the rate at which Black-owned firms accumulate capital is similar to that of White-owned firms. This latter finding led the authors to conclude that Black-owned firms are persistently disadvantaged due to differences in initial capitalization (i.e., Black-owned firms start smaller and therefore stay smaller). In contrast, we emphasize that these size differences do not necessarily imply a persistent disadvantage with regards to credit constraints. Specifically, the fact that Black- and White-owned firms operate with similar capital intensities over time implies that the differences in implicit costs do not persist. From a macroeconomics perspective, this implies that the “misallocation” of capital across Black- and White-owned firms are reduced over time.

5.2.2 ARPK Differences are Persistent

We next turn to analyzing the dynamics of the markup wedge. Our baseline specification is identical to that in Section 5.2.1, and we report our results in Figure 4 in the form of predictive margins. Looking to the general time series, we see that the differences in returns are consistent across the entire time series. This matches our hypothesis that consumer discrimination generates a persistent markup wedge, since Black entrepreneurs cannot unilaterally address this issue.

To further buttress our point, we conduct an additional analysis involving the total revenue factor productivity (TFPR) of each firm (Hsieh and Klenow (2009)). Like ARPK, TFPR is positively correlated with firm markups, and thus informative of consumer discrimination. Therefore, results using TFPR serve as an extra validation of our findings. To operationalize the computation of TFPR (which requires a stance on the parameter values of the CES production function), 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 5, which appear to corroborate our claim: TFPR of Black-owned firms is persistently lower across time.

5.2.3 Factor Supply or Customer Demand?

We briefly conclude this subsection by looking at our results in totality. On the one hand, we find that the capital cost wedge appears to shrink rapidly over time, implying that the gap in financing conditions is essentially irrelevant after four years. On the other hand, we find that demand differences are persistent over the entire sample period of eight years. In this light, we argue that demand-side factors are a relatively more important barrier towards the equalization of entrepreneurial opportunity. Importantly, holding all else constant, if all demand-side differences were eliminated, the differences in credit supply would not be a substantive barrier for the growth of Black-owned firms.

5.3 Robustness: Addressing Survivorship Bias

While we argue that the convergence in capital intensity is driven by self-accumulation of assets (that is, Black-owned firms are saving at a higher rate due to their lower initial startup capital), a threat to our argument is the possibility of survivorship bias. Specifically, to the extent that there is a specific capital intensity threshold for survival, this would mechanically lead to convergence in capital intensities without Black entrepreneurs engaging in a higher savings rate.

To address this concern, we re-conduct our analysis, but now sub-setting White-owned firms into two groups, namely a set of firms below a given cut-off of capital intensity such that they have approximately the same *initial* capital intensity at *startup*, and another set above the same cut-off. We find approximately 56% of White-owned firms fall below this threshold. Given this, we then run the following regression specification

$$\log y_{i,j,t} = \alpha + \zeta_t \times \mathcal{I}_{black} + \xi_t \times \mathcal{I}_{White,above} + X'_{i,t}\beta + \gamma_j + \theta_t + u_{i,t}, \quad (10)$$

In other words, we repeat our baseline dynamic specification, but allowing for an additional interaction term in whether the White-owned firm report a capital intensity above or below the threshold. We report our results in the form of predictive margins in Figure 6.

As a start, we first compare the predicted trajectory of White-owned firms that started with approximately the same capital intensity as Black-owned firms. Com-

paring the blue and red lines, we see that the trajectories are almost identical for the first four years. In other words, from a dynamic perspective, Black- and White-owned firms have the same rates of capital accumulation, conditional on starting with the same initial conditions. This would be a standard prediction of a typical model of investment dynamics (e.g., Moll (2014)). Consequently, initial conditions aside, we do not see a lasting impact of financial discrimination on the growth trajectory of a Black-owned firm. That said, as we observed before, for the post-financial crisis sample, we find a drop in capital intensities relative to White-owned firms who started with the same initial conditions. This again reflects our hypothesis that credit supply is rationed for Black-owned firms during the financial crisis.

To further buttress our point regarding self-accumulation, we have also overlaid the predictive margins for White-owned firms who began with capital intensities above the cut off threshold. Here, we see that their capital intensities do not vary substantially over time. This again reflects the predictions of our framework (as well as standard investment models), which is that conditional on firms being financial unconstrained, the capital intensity should be fixed over time, since the relative scarcity of capital and labor are not changing over time.

5.4 Robustness: Is the Markup Wedge Driven By Initial Conditions In Financing?

Finally, we now address the robustness of our finding regarding the dynamics of the markup wedge. Since Black-owned firms are disadvantaged in terms of their initial financial conditions, it is possible that these constraints alone could distort the initial profitability of the firm. For instance, 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, Fitzgerald, Moreira, and Priolo (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 demand simply due to their initial financial conditions.

To address this, we continue to use the subsets of White-owned firms as described earlier and re-estimate equation 10, but now replacing the dependent variable with ARPK (and controlling for the capital-labor ratio). If differences in initial conditions regarding financing is the sole (or dominant) driver of the markup wedge, we should

find a zero (or small) markup wedge between White-owned and Black-owned firms operating with the same initial capital intensities (since there is no capital cost wedge between them).

Like before, we report our results in the form of predictive margins (Figure 7). Here, we see that White-owned firms, regardless of their initial financial conditions, enjoy the same markup wedge over Black-owned firms. Consequently, it does not appear that initial disadvantages in financial conditions is a meaningful driver of the markup gap between Black- and White-owned firms.

6 Conclusion

We present a methodological framework to identify relative differences in consumer demand and credit supply across groups of firms. Using our framework, we argue that Black-owned firms face lower consumer demand and credit supply relative to White-owned firms, which we interpret as consumer and credit discrimination. However, we also find that credit constraints alone do not impede the longer term growth of successful business owners — Black individuals appear to be able to accumulate sufficient liquidity to overcome their initial lack of credit. In contrast, consumer demand differences are insurmountable by Black individuals alone.

We conclude our paper by returning to our motivation in the introduction. As we discussed, there is substantial interest in spurring entrepreneurship among Black communities, due to a belief that entrepreneurial entry and growth is key for wealth generation within Black communities. Importantly, the bulk of these policy initiatives has been to reduce credit costs for Black firms, but little emphasis is placed on studying the role of consumer demand, despite rising evidence documenting the existence of consumer discrimination.

In contrast, by documenting that credit constraints do not appear to have a persistent effect on firm outcomes, the racial wealth gap would not be a persistent fact over generations if credit discrimination was the only barrier. In contrast, persistent consumer demand discrimination would in fact be a permanent barrier to wealth accumulation, since it effectively permanently reduces the profitability of Black-owned firms. By shedding light on these two channels, we argue that policies based on subsidizing credit supply alone is unlikely to structurally shift the racial wealth gap. However, since consumer discrimination as estimated in our framework is at heart

an unexplained residual, this opens room for further research into the source of these disparities, as well as options for policy intervention.

7 Figures and Tables

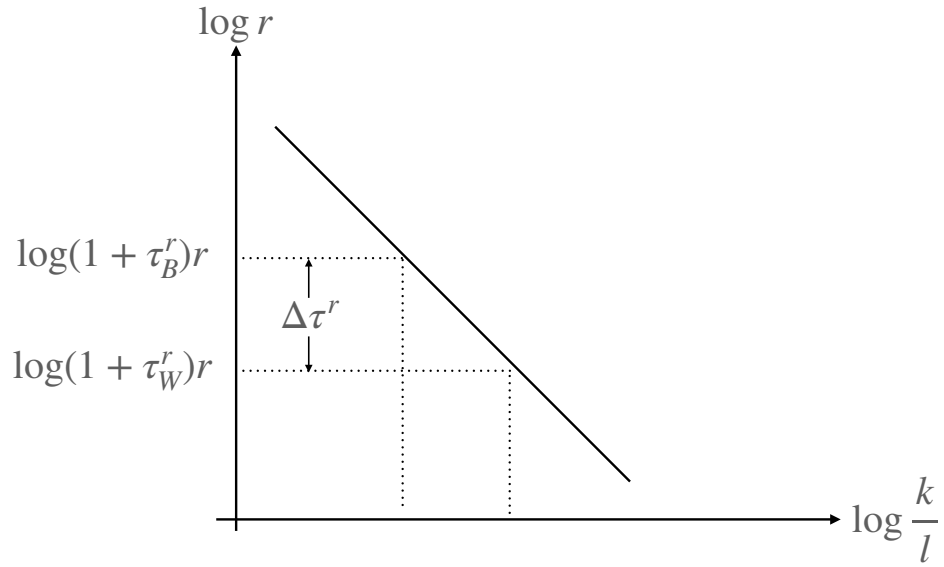


Figure 1: Capital-intensity and interest rates

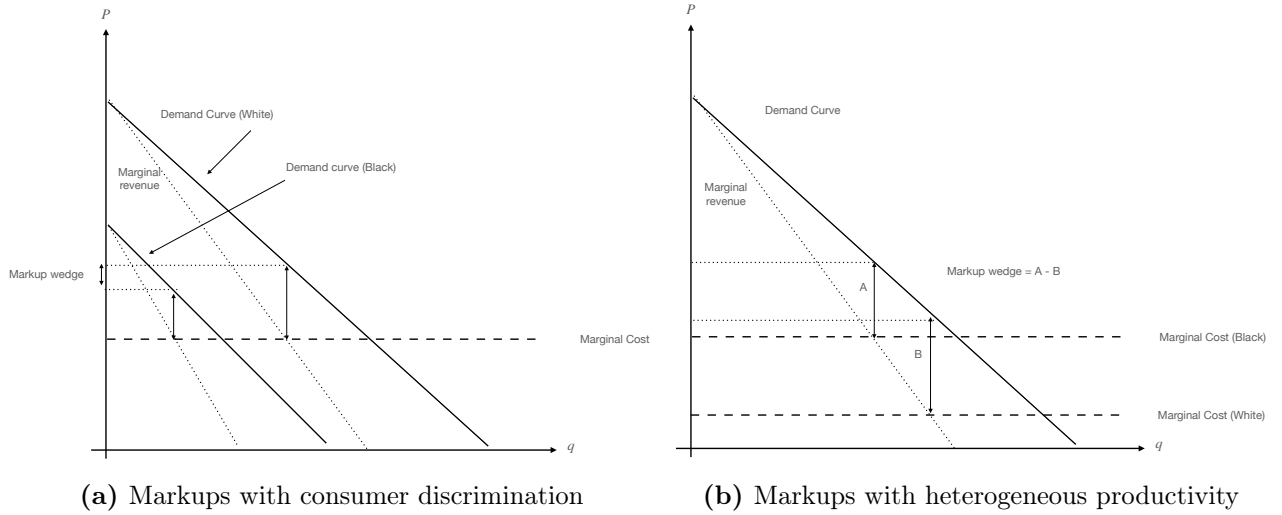


Figure 2: Markups and productivity

Table 1: Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: $\log \frac{k}{l}$				Panel B: $\log \text{ARPK}$			
δ	-0.522 (0.084)	-0.493 (0.086)	-0.281 (0.104)	-0.474 (0.109)	-0.680 (0.079)	-0.769 (0.068)	-0.630 (0.095)	-0.751 (0.095)
Controls	No	X	X, wealth	X, 2008+	No	X	X, wealth	X, 2008+
Observations	8590	8528	4386	4441	8590	8528	4386	4441
R^2	0.111	0.138	0.181	0.139	0.350	0.503	0.533	0.513
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: 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 where X additionally includes capital-labor ratio k/l . Standard errors are in parentheses. All figures are rounded to 2 significant figures or 3 decimal places where appropriate.

Table 2: Correlation of capital intensity with risk measures

	(1)	(2)	(3)	(4)
	Credit Score	PAYDEX	Financial Stress	vol of ROA
δ	0.111 (0.018)	0.166 (0.061)	0.101 (0.019)	-0.592 (0.027)
Observations	8474	4260	8626	9585
R^2	0.126	0.112	0.122	0.174
Year FE	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓

Notes: This table reports an OLS regression of the log capital-labor ratio on each given measure of risk. Standard errors are in parentheses. All figures are rounded to 2 significant figures or 3 decimal places where appropriate.

Table 3: Correlation of risk measures with race

	Credit Score			PAYDEX			Financial Stress			vol ROA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Full Sample												
δ	-0.521	-0.509	-0.615	-0.188	-0.194	-0.169	-0.401	-0.408	-0.328	0.107	0.086	0.134
	(0.063)	(0.062)	(0.097)	(0.049)	(0.051)	(0.060)	(0.079)	(0.079)	(0.113)	(0.044)	(0.044)	(0.069)
Observations	7660	7602	3831	3781	3762	2563	7784	7726	3828	8631	8569	4419
R^2	0.068	0.081	0.077	0.032	0.036	0.057	0.050	0.061	0.055	0.072	0.094	0.109
Panel B: Masters/PhD Sample												
δ	-0.812	-0.779	-0.740	-0.166	-0.158	-0.039	-0.315	-0.333	-0.178	-0.005	-0.061	-0.141
	(0.127)	(0.126)	(0.170)	(0.052)	(0.053)	(0.055)	(0.065)	(0.075)	(0.176)	(0.062)	(0.060)	(0.089)
Observations	1726	1721	896	827	824	574	1750	1745	895	1948	1943	1034
R^2	0.107	0.115	0.178	0.103	0.115	0.276	0.065	0.075	0.176	0.118	0.152	0.171
Panel C: S-Corp / LLC Sample												
δ	-0.521	-0.480	-0.541	-0.139	-0.153	-0.102	-0.261	-0.270	-0.177	-0.043	-0.041	-0.098
	(0.063)	(0.080)	(0.130)	(0.059)	(0.062)	(0.055)	(0.094)	(0.095)	(0.135)	(0.042)	(0.043)	(0.051)
Observations	7660	4733	2431	2704	2688	1813	4830	4787	2425	5333	5289	2770
R^2	0.068	0.081	0.090	0.038	0.042	0.070	0.047	0.053	0.078	0.089	0.114	0.133
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports an OLS regression of each given measure of risk on a dummy indicator that evaluates to 1 if the respondent identifies as Black, and 0 if White, for a given subset of the sample. For each risk measure, columns are “No controls”, “Controls without wealth”, and “Controls with wealth”, respectively. Standard errors are in parentheses. All figures are rounded to 2 significant figures or 3 decimal places where appropriate.

Table 4: Correlation of returns to capital with risk measures

	(1)	(2)	(3)	(4)
Credit Score	0.078 (0.020)			
PAYDEX		0.123 (0.077)		
FSSP			0.095 (0.020)	
vol of ROA				0.659 (0.028)
Observations	8510	4276	8662	9631
R^2	0.089	0.110	0.090	0.152
Year FE	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓

Notes: This table reports an OLS regression of the log ARPK on each given measure of risk. Standard errors are in parentheses. All figures are rounded to 2 significant figures or 3 decimal places where appropriate.

Table 5: How much does controlling for statistical discrimination matter?

	Baseline	Credit Score	PAYDEX	Financial Stress	vol of ROA	Advanced degree subset	S-Corp/LLC subset
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: No controls							
δ	-0.522 (0.084)	-0.385 (0.102)	-0.307 (0.143)	-0.415 (0.096)	-0.460 (0.082)	-0.001 (0.181)	-0.309 (0.128)
Observations	8590	7628	3768	7752	8590	1940	5345
R^2	0.111	0.124	0.105	0.122	0.171	0.133	0.125
Panel B: Controls							
δ	-0.493 (0.086)	-0.370 (0.104)	-0.261 (0.147)	-0.402 (0.098)	-0.443 (0.084)	0.031 (0.177)	-0.278 (0.132)
Observations	8528	7570	3749	7694	8528	1935	5301
R^2	0.138	0.152	0.121	0.149	0.197	0.175	0.136
Panel C: Controls + Wealth							
δ	-0.281 (0.105)	-0.111 (0.129)	-0.174 (0.158)	-0.135 (0.128)	-0.199 (0.106)	0.156 (0.248)	-0.138 (0.149)
Observations	4386	3806	25520	3803	4386	1027	2764
R^2	0.181	0.194	0.156	0.193	0.241	0.224	0.159
Year FE	✓	✓	✓	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓	✓	✓	✓

Note: This table reports an OLS regression of the capital-labor ratio controlling for each specific risk factor, and for different subset of the sample. Standard errors are in parentheses. All figures are rounded to 2 significant figures or 3 decimal places where appropriate.

Table 6: How much does controlling for productivity matter?

	Baseline (1)	Advanced degree (2)	S-Corp/LLC (3)
Panel A: No Controls			
δ	-0.680 (0.079)	-0.688 (0.146)	-0.619 (0.094)
Observations	8590	1940	5345
R^2	0.350	0.385	0.492
Panel B: Controls			
δ	-0.769 (0.068)	-0.805 (0.120)	-0.632 (0.082)
Observations	8528	1930	5301
R^2	0.503	0.589	0.577
Panel C: Controls + Wealth			
δ	-0.630 (0.095)	-0.880 (0.136)	-0.587 (0.131)
Observations	4386	1025	2764
R^2	0.533	0.631	0.599
Year FE	✓	✓	✓
Indus. FE	✓	✓	✓

Notes: This table reports an OLS regression of log ARPK for different subset of the sample. Standard errors are in parentheses. All figures are rounded to 2 significant figures or 3 decimal places where appropriate.

Table 7: How much does market segmentation matter?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: $\log \frac{k}{l}$				Panel B: $\log \text{ARPK}$			
δ	-0.534 (0.091)	-0.516 (0.093)	-0.262 (0.116)	-0.483 (0.122)	-0.612 (0.083)	-0.714 (0.071)	-0.503 (0.098)	-0.650 (0.099)
ν	0.095 (0.239)	0.192 (0.245)	-0.127 (0.260)	0.066 (0.265)	-0.557 (0.245)	-0.460 (0.215)	-0.832 (0.260)	-0.691 (0.272)
Observations	8,590	8,528	4,386	4,441	8,590	8,528	4,386	4,441
R^2	0.111	0.138	0.181	0.139	0.350	0.504	0.535	0.514
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table reports our estimation results per equation 8, where the coefficient of interest is ν . 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. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

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 9.

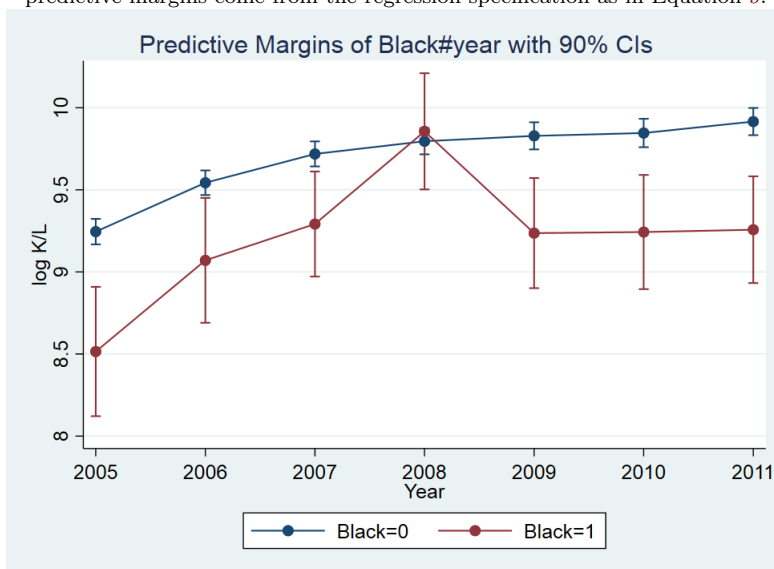


Figure 3: Average log capital-labor ratio over time.

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 9.

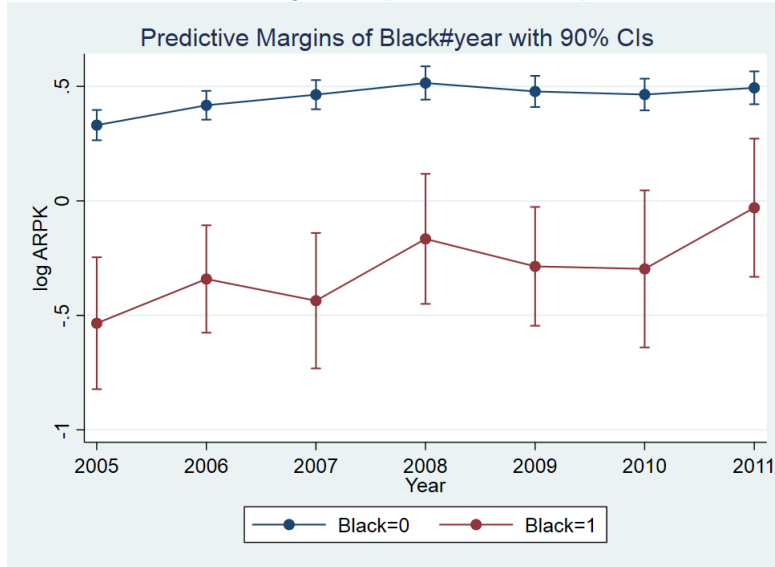


Figure 4: Average log ARPK over time.

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 9.

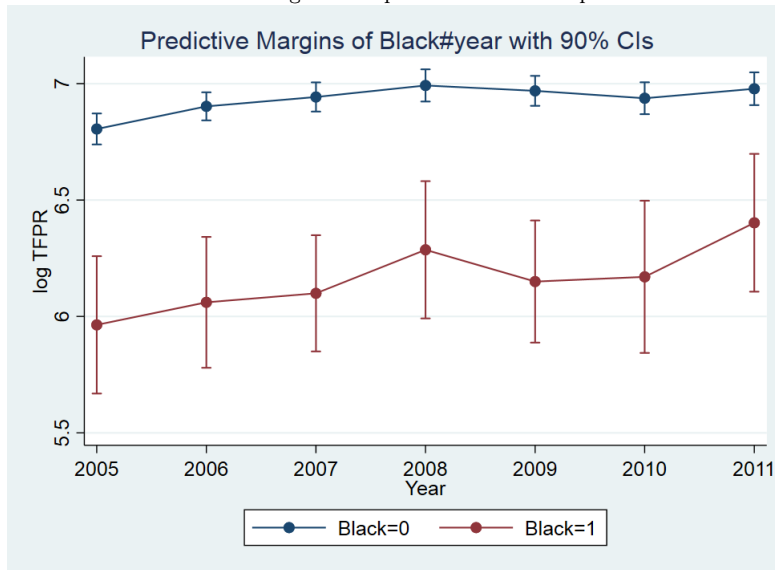


Figure 5: Average log TFPR over time.

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 10.

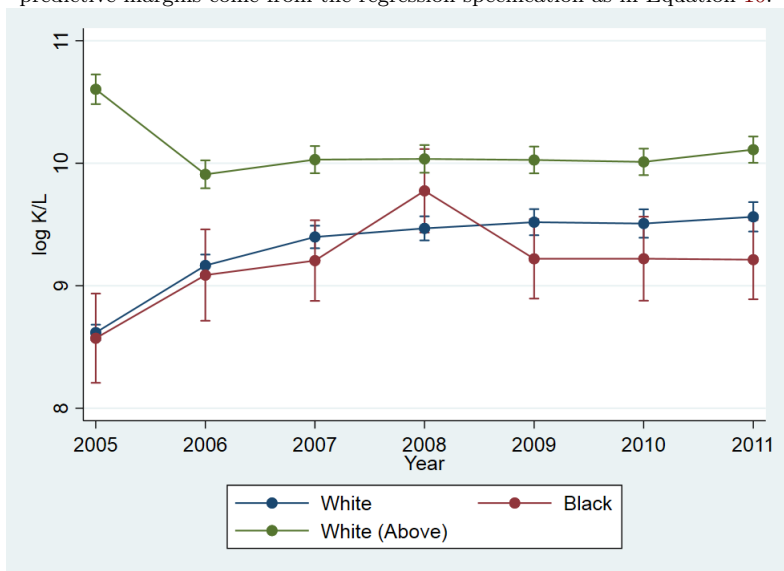


Figure 6: Average log K/L over time for firms with the same initial K/L.

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 10.

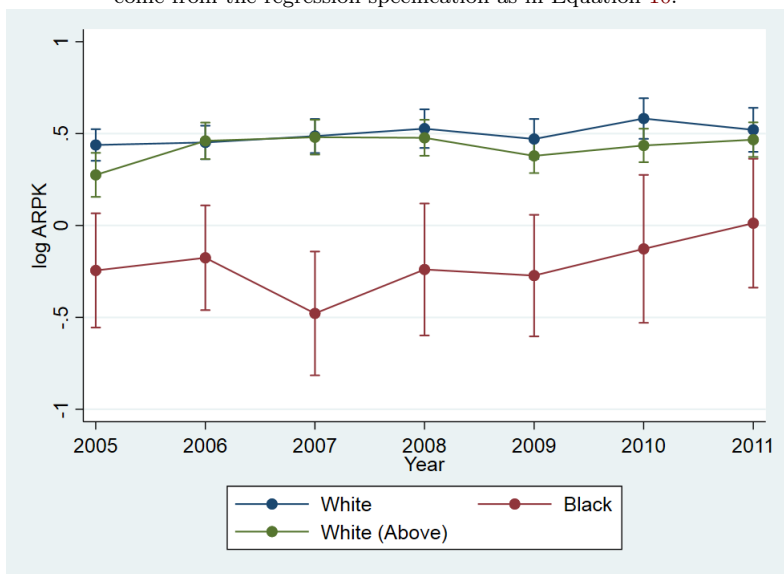


Figure 7: Average log ARPK over time for firms with the same initial K/L.

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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,

$$MRPK \equiv \frac{\partial p(y, d, \tau_g^d)y}{\partial k} = (1 + \tau_g^r)r, \quad (11)$$

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

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

$$\frac{\partial p(y, d, \tau_g^d)y}{\partial k} = \frac{\partial p}{\partial y} \frac{\partial y}{\partial k} y + \frac{\partial y}{\partial k} p \quad (12)$$

$$= \frac{\partial y}{\partial k} \left(\frac{\partial p}{\partial y} y + p \right). \quad (13)$$

Next, keeping in mind that

$$ARPK \equiv \frac{py}{k},$$

the ratio of MRPK to ARPK is given by

$$\frac{MRPK}{ARPK} = \frac{\partial y / \partial k}{y/k} \left(\frac{\partial p / \partial y}{p/y} + 1 \right) \quad (14)$$

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 μ 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,

$$\frac{\partial p(y, d, \tau_g^d)y}{\partial l} = \frac{\partial y}{\partial l} \left(\frac{\partial p}{\partial y} y + p \right) = w \quad (15)$$

Next, by dividing equation 2 by 15 (and with slight abuse of notation), we obtain

$$\frac{\partial l/\partial k}{l/k} \frac{l}{k} = \frac{(1 + \tau_g^r)r}{w}. \quad (16)$$

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. Standard cost minimization implies that

$$\frac{k}{l} = \left(\frac{\alpha}{1 - \alpha} \frac{w}{(1 + \tau_g^r)r} \right)^\eta, \quad (17)$$

where α and η are the capital-intensity and elasticity of substitution parameters of the CES function respectively. This implies that the capital-labor ratio is only a function of r , w , and τ_g^r . In turn, this implies that $\epsilon_{k,l}$ is also trivially a function of

r , w , and τ_g^r .

Moreover, with the CES production assumption, we can derive the following expression,

$$\begin{aligned}\epsilon_k &= \alpha \left(\frac{y}{k}\right)^{\frac{\eta-1}{\eta}} \\ &= \alpha \left(\alpha + (1-\alpha) \left(\frac{l}{k}\right)^{\frac{\eta-1}{\eta}}\right)^{-1}.\end{aligned}\tag{18}$$

But as we have already derived, the capital-labor ratio depends only on r , w , and τ_g^r ; and consequently, ϵ_k also depends only on r , w , and τ_g^r . Moreover, increases in τ_g^r leads to a decrease in the capital-labor ratio, which in turn leads to a decrease in ϵ_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 Robustness of Identification Strategy to Factor Adjustment Costs

C Data Source and Summary Statistics

C.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 *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.

C.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.

C.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.

C.II.2 Summary statistics

We report our summary statistics in Table 8 below.

Table 8: 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.

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

D 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.

D.I Capital-Labor Ratio Results

D.I.1 Full Time Workers only

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

Table 9: Capital-labor ratio

	(1)	(2)	(3)	(4)
δ	-0.470 (0.084)	-0.451 (0.087)	-0.228 (0.105)	-0.444 (0.111)
Observations	8585	8523	4383	4438
R^2	0.114	0.146	0.191	0.142
Year FE	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓

Note: 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. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

D.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 10: Capital-labor ratio

	(1)	(2)	(3)	(4)
δ	-0.692	-0.661	-0.466	-0.661
	(0.105)	(0.106)	(0.128)	(0.136)
Observations	5037	5001	2487	2506
R^2	0.147	0.177	0.221	0.172
Year FE	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓

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. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

D.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 11: Capital-labor ratio

	(1)	(2)	(3)	(4)
δ	-0.628	-0.612	-0.432	-0.633
	(0.107)	(0.109)	(0.134)	(0.140)
Observations	5032	4996	2484	2503
R^2	0.149	0.167	0.195	0.147
Year FE	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓

Note: 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. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

D.II ARPK Results

D.II.1 Employer firms only

Table 12: ARPK

	(1)	(2)	(3)	(4)
δ	-0.789	-0.836	-0.721	-0.859
	(0.106)	(0.090)	(0.130)	(0.134)
Observations	5037	5001	2487	2506
R^2	0.350	0.446	0.494	0.461
Year FE	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓

Note: 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. Standard errors are in parentheses. All figures are rounded to 3 decimal places.

E 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 8](#), 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.

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, Levine, and Leonard (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 13, 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 13: Capital-wage bill ratio

	(1)	(2)	(3)	(4)
δ	-0.767 (0.101)	-0.810 (0.087)	-0.707 (0.123)	-0.850 (0.127)
Observations	5032	4996	2484	2503
R^2	0.372	0.457	0.517	0.483
Year FE	✓	✓	✓	✓
Indus. FE	✓	✓	✓	✓

Note: 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. Standard errors are in parentheses. All figures are rounded to 3 decimal places.