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

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Abstract

We formulate a framework showing that differences in capital returns and capital intensity between groups of firms can identify relative differences in consumer demand and credit constraints. Using micro-data on Black- and White-owned startups, we find robust evidence that Black-owned startups have lower capital returns, implying that Black-owned startups face lower consumer demand due to race. In contrast, we find mixed evidence of tighter credit constraints due to race. We further show that differences in capital returns are persistent over time, whereas capital intensity differences are transitory. This suggests that lower demand, rather than credit constraints, might be the main barrier to growth for Black-owned startups. (*JEL* E22, J15, L26)

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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 because of 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 as a barrier to successful Black-entrepreneurship in the broader market are sparse. In this paper, we study whether disparities in consumer demand and credit supply across Black- and White-owned startups are prevalent at an economy-wide level, whether one channel is more dominant than the other, and whether policies focusing on credit supply alone are sufficient to promote sustainable long-term Black entrepreneurship.

To answer our questions, we present a stylized theoretical framework in which entrepreneurs decide on how much capital and labor to hire to maximize profits, subject to a demand function with non-constant price elasticities, and in which Black entrepreneurs face consumer and credit discrimination. We derive a set of 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 lower consumer demand on the basis of race alone, but mixed evidence of tighter credit constraints. Crucially, we also find that Black entrepreneurs are able to overcome their initial credit constraint over time, but consumer demand is persistently lower relative to that of White-owned firms. This suggests that policies focused solely on raising credit supply for Black entrepreneurs can accelerate existing

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

firms to their optimal unconstrained firm sizes but are unlikely to address the fundamental barrier to success for Black entrepreneurship.

Identifying the existence of race-based barriers 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 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 do not exist. Our main methodological contribution is to emphasize how, using standard accounting data alone, one can identify (at 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 the assumption that firms face downward sloping demand curves with non-constant price elasticities. Within this framework, we show that the average differences in capital intensity (ratio of capital to labor) and average differences in the average revenue product of capital (ratio of revenue to capital) can be jointly used to identify the presence of credit and 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. We show that a firm facing discrimination would face a higher implicit capital cost, and thus operate with a lower capital-labor ratio relative to that of an otherwise identical firm that does not face discrimination.

Identification of consumer demand differences follows similarly. In this case, 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, holding all else constant.

Taking these predictions to the data, we find that compared with White-owned firms, Black-owned firms operate with higher implicit capital costs and lower markups. Our most conservative estimates imply that Black-owned firms face about 10% higher borrowing costs, and 41% lower markups. Moreover, interpreting the markup gap as a difference in the return to capital, a back-of-the-envelope calculation suggests that the markup gap could translate into a 1.71 times difference in the average market value of White- and Black-owned firms, suggesting that differences in consumer demand could be an important determinant of the racial wealth gap, at least as it pertains to that within the population of entrepreneurs.

We find that our results regarding markup differences 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 because of 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 multiple confounding effects, and find that accounting for these effects does not change our conclusion.[2] Moreover, we leverage multiple sub-sample analyses to argue that the difference in markups we identify is due to consumer discrimination. In contrast, our findings regarding capital costs differences appear largely explained by wealth and risk differences between Black and White entrepreneurs. Therefore, to a large extent, the statistical difference in capital cost we uncover appears due to historical differences in Black and White entrepreneurs, rather than racial animosity on the part of credit providers.

Our cross-sectional results imply the existence of both channels as barriers to growth

[2] Among others, we consider differential productivity, differential internal financial resources, market segmentation, differential riskiness, and negative selection.

for Black-owned startups, but do not inform us of the relative importance of each channel. Moreover, they do not reject the possibility that credit differences alone are 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 its constraints through asset accumulation (e.g., Moll (2014)). A dominant credit constraint channel would imply slow rates of convergence; moreover, if the gap in markups is fundamentally due to credit constraints, then it would also fade out over time.

We operationalize this insight in two ways. First, we simply estimate the gap in capital cost and markups on a year-by-year basis, and track the changes over time. Here, we find that the gap in capital cost rapidly disappears over four years, whereas the gap in markups is stable over the same period of time. This suggests that despite the initial differential access to capital, Black entrepreneurs quickly accumulate enough assets to outgrow their disadvantage. Conversely, the differences in markups do not dissipate despite a narrowing of the gap in capital cost.

Second, we divide our sample of White-owned firms into a subset of firms reporting no gap in capital cost relative to Black-owned firms, and a complement subset with a gap in capital cost, and repeat our earlier year-by-year estimation. 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 differences differentially affect the growth trajectory of Black-owned firms.

We find that the gap in markups, at the initial year of founding, is almost 50% larger when comparing Black-owned firms with the subset of White-owned firms with a capital cost gap, relative to the complement subset without a capital cost gap; moreover, these differences are statistically significant. Furthermore, we find that the differences in the gap in markups narrow over the course of the years when the gap in capital cost disappears, and become statistically indistinguishable from zero.

Taken in totality, these results imply that race-based credit constraints alone do not differentially affect the ability of Black entrepreneurs to accumulate assets, whereas the differences in consumer demand could permanently affect the profitability of Black-owned firms. Thus, we believe that policy tools based on increasing credit supply alone are unlikely to promote sustainable long-term Black entrepreneurship. However, because we find that capital supply does influence the size of the gap in markup, we believe that policy tools based on increasing credit supply continue to be an important tool. Moreover, keeping in mind that the demand differences we uncover are, at heart, a residual, we contend that further research on the direct source of these demand differences, and strategies to alleviate them, could be 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 introduce our data source, and in Section 4, we present our main empirical results utilizing a cross-sectional analysis. 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 has documented that Black online vendors charge lower prices for identical goods (e.g., Doleac and Stein (2013) on eBay 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 between this observation and 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 data set. 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 that of recent research highlighting the importance of group-based demand-side differences (Hardy and Kagy (2021)).

Third, our paper builds on, and adds to, the macroeconomic literature on factor misallocation and misallocation driven by discrimination in particular. 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 are crucial to identifying these two channels separately. In this respect, we differ from the statistical approach to studying disparities in outcomes across races in entrepreneurship adopted by the labor economics literature (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 (2022a); Morazzoni and Sy (2022); Bento and Hwang (2022b)). Importantly, by admitting a more general demand structure, we depart from the common identification argument in macroeconomics that connects an unconditional positive correlation between higher returns to capital and tighter financial constraints (e.g., Bento and Hwang (2022a); Morazzoni and Sy (2022); Goraya (2023)).

Finally, our paper contributes to ongoing macroeconomic 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)) has documented a large and persistent gap in wealth between Black and White households and, in addition, found that a substantial driver of this gap is a permanent difference in earnings and returns to investment. Our paper is complementary to this research in that it documents that Black entrepreneurs have 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 Karabarbounis (2022), who argue that Black entrepreneurs underinvest in their own businesses because of 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 $g(i) \in \{W, B\}$, where W and B stand for White and Black-owned 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, and a group-specific fixed effect τ_g^d, all of which three 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.*

Assumption 2. ***(Marginal Revenue)*** *The price elasticity of demand is weakly decreasing in d_i and weakly increasing in prices.*

Assumption 3. ***(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, in which the total implicit (shadow) cost of capital is given by $(1 + \tau_g^r)r_i$, and the total implicit (shadow) cost of labor is given by $(1 + \tau_g^l)w_i$. All entrepreneurs have the same productivity in producing physical output.*

Assumption 4. ***(Uncertainty)*** *There is no uncertainty associated with firm production or demand.*

The first two assumptions summarize the demand structure that firms in our model face. They imply 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 so that higher values correspond to higher demand for individual i's or group g's product. In this context, consumer discrimination refers to the case in which $\tau_B^d - \tau_W^d < 0$; in other words, White-owned businesses can charge a higher price relative to that charged by Black-owned businesses for the exact same product. Importantly, we do not assume any specific market structure, so long as the given market structure is consistent with the above assumptions. Notably, assumption 2 is consistent with recent empirical findings that markups are increasing in firm size and productivity (e.g., Edmond, Midrigan, and Xu (2022)). These assumptions, along with the assumption that all entrepreneurs have the same productivity and face no uncertainty, imply the following corollary:

Corollary 1. *If $\tau_B^d - \tau_W^d < 0$, then the average markup charged by a Black-owned business is lower than that of a White-owned business.*

Our next two assumptions about production choices and uncertainty follow Hsieh and Klenow (2009). In this context, higher τ_g^r implies that firms from group g face higher total costs of capital, regardless of individual characteristics. For instance, Black entrepreneurs might face financial discrimination, perhaps because they are charged higher interest rates (explicit) or face higher probabilities of loan denials (implicit). Similarly, higher τ_g^l implies that firms from group g face higher total costs of labor. This might happen if Black entrepreneurs face difficulty hiring in the labor market due to aversion by other groups towards working for a Black-owned firm. While our paper does not focus on studying hiring frictions per se, we include this assumption given recent research suggesting hiring frictions for Black entrepreneurs (e.g., Bento and Hwang (2022a)).

Note that assumption 3 also allows for the shadow cost of capital and labor to vary by individual. For instance, a less wealthy individual might face a higher shadow cost of capital because they are unable to fully capitalize their firms via internal and external financing, or because they face higher costs of borrowing due to lower collateral availability. Likewise, in the case of labor, heterogeneity in the cost of labor might happen if individuals face segmented labor markets. We allow for these possibilities to aid exposition later in this section when we address key issues to identification using our framework.

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

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

where we suppress the subscript i for notational ease. We now derive three formal sets of relationships. All derivations and proofs for the rest of the paper are in Appendix A.

First, a profit-maximizing firm always sets its marginal revenue product of capital (MRPK) to its implicit cost of capital, and its marginal revenue product of labor (MRPL) to its implicit cost of labor, given by the following pair of equations:

$$MRPK = (1 + \tau_g^r)r, \tag{2}$$

$$MRPL = (1 + \tau_g^l)w. \tag{3}$$

Importantly, this is true regardless of market structure. This implies that a direct measurement of a firm's MRPK (MRPL) is directly revealing of the firm's cost of capital (cost of labor), and thus the extent of the discrimination it faces. However, because direct measurement of MRPK (MRPL) is essentially impossible, researchers typically operationalize this insight by using the *average* revenue product of capital and labor (ARPK and ARPL respectively) as proxies for MRPK and MRPL.

Our second derivation relates ARPK (ARPL) to MRPK (MRPL) through the following formula:

$$\log ARPK = \log MRPK + \log\left(1 + \mu\left(\tau_g^d, d\right)\right) - \log \epsilon_k, \tag{4}$$

$$\log ARPL = \log MRPL + \log\left(1 + \mu\left(\tau_g^d, d\right)\right) - \log \epsilon_l. \tag{5}$$

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 directly on both individual specific-characteristics (d_i) that are independent of race, and on race itself (τ_g^d).

Thus, for notational ease, we will denote markups as μ_{ig} going forward. Next, ϵ_k and ϵ_l are the elasticities of physical output with respect to capital and labor respectively, and arise only from the production side of the equation.

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

$$\log \frac{k}{l} = \log \epsilon_{k,l} - \log r - \log\left(1 + \tau_g^r\right) + \log w + \log\left(1 + \tau_g^l\right). \tag{6}$$

Here, $\epsilon_{k,l}$ is an elasticity term capturing the marginal rate of technical substitution for a given level of output. Like ϵ_k and ϵ_l, this term arises entirely from the production side of the equation.[3]

With these relationships, we can derive a simple result in relation to the elasticity terms as summarized in Lemma 1. We will leverage this in our identification strategy.

Lemma 1. *If Assumptions 1, 3, and 4 hold, then the elasticity terms, ϵ_k, ϵ_l, and $\epsilon_{k,l}$ do not depend on the market structure. Therefore, for a given production technology, variations in the capital-labor ratio reflect only variations in the relative shadow cost of capital to labor, and are unaffected by variations in markups.*

Finally, to set notation for the discussion (and for the rest of the paper), we formalize the following definitions.

Definition 1. *A markup wedge is defined as $\Delta\mu \equiv \mathbb{E}\left[\log(1 + \mu_{ig})|g = B\right] - \mathbb{E}\left[\log(1 + \mu_{ig})|g = W\right]$. If consumer discrimination exists, then $\Delta\mu < 0$.*

Definition 2. *A capital wedge is defined as $\Delta\tau^r \equiv \log(1 + \tau_B^r) - \log(1 + \tau_W^r)$. If credit discrimination exists, then $\Delta\tau^r > 0$.*

Definition 3. *A labor wedge is defined as $\Delta\tau^l \equiv \log(1 + \tau_B^l) - \log(1 + \tau_W^l)$. If labor discrimination exists, then $\Delta\tau^l > 0$.*

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

2.2 Identification of Wedges

In this subsection, we lay out our econometric framework to jointly recover the markup, capital, and labor wedges using purely reduced form approaches similar to Hsieh and Klenow (2009).[4]

2.2.1 Summary of Econometric Framework

In a nutshell, our methodology leverages cross-equation restrictions implied by Equations 4 to 6 to identify the three wedges. In the interest of exposition, we first present the procedure—a two step estimator approach— then discuss the logic.

In the first step, we jointly estimate the following system of equations,

$$y_{i,j,t} = \alpha + \delta \times \mathcal{I}_{black} + \varsigma \log \left(\frac{k}{l}\right)_{i,j,t} + \eta \log w_{i,t} + X'_{i,t}\beta + \gamma_j + \theta_t + u_{it}, \tag{7}$$

where $y_{i,j,t} \equiv \begin{bmatrix} \log ARPK_{i,j,t} \\ \log ARPL_{i,j,t} \end{bmatrix}$, $\alpha \equiv \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix}$ refers to the intercept term, $\log\left(\frac{k}{l}\right)$ refers to the capital-labor ratio and $\log w$ refers to firm-specific wage rates (both terms are scalars), $X_{i,t}$ a vector of individual-specific control variables, $\gamma_j \equiv \begin{bmatrix} \gamma_{1,j} \\ \gamma_{2,j} \end{bmatrix}$ and $\theta_t \equiv \begin{bmatrix} \theta_{1,t} \\ \theta_{2,t} \end{bmatrix}$ are industry and year fixed effects, respectively, $u_{it} \equiv \begin{bmatrix} u_{1,i,t} \\ u_{2,i,t} \end{bmatrix}$ is the error term, and finally $\mathcal{I}$ is an indicator variable (a scalar) that evaluates to 1 if the individual is a Black entrepreneur, and 0 otherwise. $\delta \equiv \begin{bmatrix} \delta^{\mu}_{arpk} \\ \delta^{\mu}_{arpl} \end{bmatrix}$ is our estimate of interest. Importantly, we estimate the system of equations subject to the cross-equation restriction that $\delta^{\mu} \equiv \delta^{\mu}_{arpk} = \delta^{\mu}_{arpl}$, and use δ^{μ} as an estimator for $\Delta\mu$.

[4] While not a focus of our paper, we also view our framework as providing a methodological contribution relative to the current "misallocation" literature, for which these wedges are typically *under-identified*, and necessitate normalization of one of these wedges.

In the second step, we then use our estimate for $\Delta\mu$ to compute markup-adjusted ARPK and ARPL, namely

$$\log \widetilde{ARPK}_{i,j,t} = \log ARPK_{i,j,t} - \delta^{\mu} \times \mathcal{I}_{black}, \tag{8}$$

$$\log \widetilde{ARPL}_{i,j,t} = \log ARPL_{i,j,t} - \delta^{\mu} \times \mathcal{I}_{black}. \tag{9}$$

With the markup-adjusted ARPK and ARPL, we then jointly estimate the following system of equations,

$$y_{i,j,t} = \alpha + \delta \times \mathcal{I}_{black} + \eta \log w_{i,t} + X'_{i,t}\beta + \gamma_j + \theta_t + u_{it}, \tag{10}$$

where the notation is largely similar to that of Equation 7, except that $y_{i,j,t} \equiv [\log \widetilde{ARPK}_{i,j,t}, \log \widetilde{ARPL}_{i,j,t}, \log \left(\frac{k}{l}\right)_{i,j,t}]'$, and thus the various vectors and matrices have one extra row relative to those in Equation 7. Furthermore, we impose that $\eta = [0, \eta_2, \eta_3]'$; that is, we do not allow wages to have an effect on markup-adjusted ARPK. Finally, $\delta \equiv [\delta^r, \delta^l, \delta^{r/l}]'$ is our estimate of interest. Importantly, we estimate the system of equations subject to the cross-equation restriction that $\delta^{r/l} = \delta^l - \delta^r$; in turn, we use δ^r and δ^l as our estimates for $\Delta\tau^r$ and $\Delta\tau^l$ respectively.

2.2.2 Logic of Econometric Framework

The first step of our approach draws from two aspects of our model. First, we note that even with a perfect set of controls in $X_{i,t}$, one cannot identify the markup wedge through a regression of either $\log ARPK$ or $\log ARPL$ on the race indicator variable alone because the capital and labor wedges, respectively, confound the analysis. For instance, a Black-owned firm facing both consumer and credit discrimination might report an ARPK that is identical to a White-owned firm if both forces cancel out each other. A similar effect with the labor wedge confounds identification.

That said, from Equation 6, we see that the capital-labor ratio can at least act as an imperfect proxy for τ_g^r and τ_g^l. Crucially, via Lemma 1, we see that it is uncorrelated with markups. Therefore, controlling for systematic differences in the capital-labor ratio across racial groups, as we do so in Equation 7, permit identification of $\Delta\mu$. However, because the capital-labor ratio is an imperfect proxy, our estimate of the markup wedge is likely attenuated; that is, δ^μ is likely an underestimate of $\Delta\mu$.

Second, because $\log ARPL - \log ARPK = \log\left(\frac{k}{l}\right)$ is an identity, if $\log ARPK$, $\log ARPL$, and $\log\left(\frac{k}{l}\right)$ are constructed as-is from the raw data without further data treatment, δ^μ_{arpk} and δ^μ_{arpl} are *guaranteed* to be identical. Therefore, in theory, one can recover the markup wedge simply using either ARPK or ARPL alone as the dependent variable. However, in practice, we always winsorize our dependent variables to avoid outliers from distorting our analysis. This creates statistical noise that breaks the identity, which we overcome via the constrained estimation approach we presented above.

The second step of our procedure adjusts the average revenue products by the markup wedge such that racial differences in the residual average revenue products are now due solely to τ_g^r and τ_g^l. Therefore, in principle, with the adjusted average revenue products, we can directly obtain the capital and labor wedges by simply estimating, separately, the first two lines of 10.

That said, our framework allows for over-identification of either wedges; namely Equation 6 provides an additional cross-equation restriction. Specifically, given an estimate of the capital and labor wedge, the differences between the two must be equal to the racial gap in the capital-labor ratio itself. Therefore, we estimate a constrained system of equations to obtain an internally consistent estimate for both wedges. Moreover, we restrict that wages have no effect on ARPK through the logic of Equation 4, and we remove the capital-labor ratio as a control variable since our goal is now to explicitly estimate the capital and labor wedges.

2.2.3 Connecting Our Model to Extant Research

There is now a budding literature in macroeconomics emphasizing the identification and quantification of financial frictions as barriers to entrepreneurship for groups facing discrimination (see, for instance, Bento and Hwang (2022a), Morazzoni and Sy (2022), and Goraya (2023) for recent research on financial discrimination by race, gender, and caste respectively). We now use our theoretical discussion to clarify two key issues that might confound inference on financial discrimination for current research.

On the one hand, 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-owned firms. These micro-estimates are sometimes then used for input into calibrated macroeconomic models (e.g., Bento and Hwang (2022a)). Our theoretical model shows that a Black-owned firm would be smaller than a White-owned firm even if it did not face financial discrimination, so long as it also faced consumer discrimination. Instead, we argue that a distortion of the factor mix (i.e., capital-labor ratio) is key for identifying financial discrimination.

On the other hand, recent papers in the macroeconomics literature (e.g., Morazzoni and Sy (2022); Goraya (2023)) 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. Our framework presents a simple solution to this problem via the two-step estimator we presented.[5]

2.3 Challenges to Identification

Endogeneity in the regressors is a prevalent problem in any empirical analysis. In our paper, our hypothesis is that δ^{μ} and δ^{r} (the empirical objects we can estimate) are unbiased

[5]While not the focus of our paper, a similar issue arises if one wishes to identify hiring frictions using differences in ARPL alone (e.g., Bento and Hwang (2022a)).

estimates of $\Delta\mu$ and $\Delta\tau^r$ (the theoretical objects of interest that we define as consumer and credit discrimination). However, a key threat to identification is that race itself is correlated with confounding variables that are not themselves due to discrimination in the current environment. Therefore, δ^μ and δ^r might be biased estimates of $\Delta\mu$ and $\Delta\tau^r$.

In this subsection, we briefly summarize the key confounding factors that can affect identification of $\Delta\tau^r$ and $\Delta\mu$ using our estimation approach. The overarching concern is that historical factors that have disenfranchised the Black population in America might have also negatively impacted the ability of Black entrepreneurs to perform as well as White entrepreneurs. In this case, even absent discrimination in the current environment, we would continue to detect a capital and markup wedge. This means that our results are always biased towards uncovering $\delta^r > 0$ and $\delta^\mu < 0$, leading to an over-interpretation of these estimates as identifying discrimination.

Therefore, for most of Section 3, after presenting our headline result with a minimal set of controls, we draw on this discussion and attempt to address these issues by running an extensive list of robustness exercises. Regardless, realistically, we cannot rigorously establish causality because of the nature of the data sources available to us (which we discuss in Section 3). Therefore, from a bigger picture perspective, we view uncovering $\delta^r > 0$ and/or $\delta^\mu < 0$ as important in the broader context of barriers to growth: The fact that these barriers exist, regardless of whether they are explicitly due to discrimination or simply historical factors, continues to be relevant to the policy discussion on equalizing opportunities for entrepreneurs of all demographics.

2.3.1 Challenges to Identifying the Capital Wedge As Discrimination

There are at least two main issues with interpreting $\delta^r > 0$ as due to discrimination (i.e., mapping an estimate of $\delta^r > 0$ into $\Delta\tau^r > 0$).

First, as already pointed out in our introduction, Black households have relatively less wealth because of the racial wealth gap. The decreased ability to self-finance will lead us to detect a positive wedge, but lead us to attribute this to racial discrimination in credit markets.

Second, and in a similar vein, if Black entrepreneurs have less wealth as collateral, or lower experience due to other historical societal factors that impede human capital accumulation, then financial lenders might be less willing to extend credit, owing simply to the higher riskiness and lower expected profitability of the firm. Again, we over-attribute the capital wedge to credit discrimination rather than historical factors. In general, we attempt to control for these effects by using a battery of control variables in the vector $X_{i,t}$, or conducting sub-sample analyses where the human capital gap is arguably less distinct. We will address such confounding effects in further detail in the empirical section.

Challenges with interpreting $\delta^r > 0$ as due to a distortion in the factor mix Albeit not a "threat to identification", a parallel issue at hand is that heterogeneity in the production function itself might be a threat to our interpretation of $\delta^r > 0$ as a distortion to the cost of capital (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 because of differential capital constraints. For example, in the extreme case where individuals perfectly bypass their capital constraints through sorting, this would imply that $\tau_g^r = 0$ and all heterogeneity in the capital-labor ratio comes through $\epsilon_{k,l}$. Consequently, δ^r would pick up differences in $\epsilon_{k,l}$. Regardless, if credit discrimination is the source of this endogenous sorting, then an estimate of $\delta^r > 0$ continues to qualitatively detect credit discrimination, except that the interpretation is no longer strictly about implicit capital cost differences.

2.3.2 Challenges to Identifying the Markup Wedge As Discrimination

As with identifying credit discrimination, the threat to identification for consumer discrimination can be phrased as follows: Assuming there is no racial animosity of White consumers towards Black entrepreneurs, would we continue to observe a markup wedge? The answer is a qualified yes, and we will discuss the reasons below. As such, our results must generally be seen as an upper-bound to the effect of consumer discrimination.

There are two key confounding effects. First, long-running racial disparities in the quality of education and labor markets might reduce the human capital of Black entrepreneurial firms. As a result, Black-, relative to White-owned firms, might simply have lower productivity, which 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 systematic differences in *physical* productivity—the ability to make the same product at a lower cost—are a substantial issue. Specifically, note that higher physical productivity translates into lower marginal costs for firms, but does not affect consumer demand. Therefore, under the assumption of identical demand (i.e., no consumer discrimination), higher physical productivity firms charge a higher markup but also simultaneously charge lower prices due to lower marginal costs (right panel of Figure A1 in Appendix D illustrates this argument). 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, we emphasize that in the empirical section, we will extensively address such confounding effects.

While we argue that differences in physical productivity are unlikely to be a confounding effect, a parallel threat to our identification of consumer discrimination is the fact that systematic differences in *revenue* productivity—the pricing power of firms for the same physical product—would also give rise to a markup wedge.[6] For instance, if human capital affects the ability to acquire customer capital (e.g., Moreira (2016)), our argument in the preceding paragraph, which relies on fixed demand curves, would no longer hold.

[6] See Foster, Haltiwanger, and Syverson (2008) for a detailed discussion of physical and revenue productivity.

Second, heterogeneity in demand across races can also arise without discrimination. For instance, it is possible that due to homophily, Black and White entrepreneurs are more likely to attract customers of their own race. Similarly, recent research has documented that Black and White households differentially sort into Black and White dominant neighborhoods due to homophily (e.g., Aliprantis, Carroll, and Young (2022)). Notably, historical societal factors have led to a large disparity in income between the Black and White populations; namely, Black consumers have lower disposable income. Likewise, it is well-documented that neighborhoods with a predominantly Black population also have lower average incomes. In this case, this implies that we would continue to observe a markup wedge, because the typical purchasing power of a customer for a Black-owned firm is lower. A similar argument can be made for the racial wealth gap as a source of the markup wedge.

In general, much of the empirical discussion in Section 3 will involve research designs devoted to addressing these issues. That said, we cannot rigorously attribute an estimate of $\delta^{\mu} < 0$ to consumer discrimination, because there is no data set that can realistically allow us to perfectly control for all these confounding effects. Therefore, in this context, we emphasize that δ^{μ} is at heart a residual, and note that the term "consumer discrimination" is used as in the literature to imply an unexplained residual that is correlated with race (e.g., Borjas and Bronars (1989); Bento and Hwang (2022a)).

With these considerations in mind, we now turn to our empirical section to assess the relative importance of consumer demand and credit supply as a barrier to growth for Black entrepreneurs.

3 Data

In this section, we introduce our primary data source and provide brief statistics associated with our data. In our robustness analyses, we will introduce additional data sources that we use to supplement our primary analysis.

3.1 The Kauffman Firm Survey

Our primary analysis draws on data from the Kauffman Firm Survey (KFS). The KFS is a single-cohort panel survey consisting of firms that were formed in the year 2004 in the United States, and tracked through 2011. The universe of firms considered for survey inclusion consisted of all newly registered firms in 2004 from the Dun and Bradstreet database, followed by a series of conditions. The KFS is a large survey, is designed to be representative of all startups in the year 2004, and provides extensive details on survey respondents. For the purposes of our paper, we focus on the revenue, assets, and 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). We focus our analysis only on the subset of firms encoded as Black-owned or White-owned. Finally, we always pool our panel for all our cross-sectional analysis in the next section.

3.2 Main Variables of Interest

Drawing from our theoretical framework, we focus our analysis on estimating the differences in ARPK, ARPL, 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. Our sample of interest includes only firms with at least $1000 in non-cash assets. For labor, an 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.[7] We further report in Appendix E.V a sequence of robustness checks in which we vary the definition of labor.

[7] Because firms hire a mix of full- and part- time workers, we further assume that each part-time worker is equivalent to one-half of a full-time worker.

Finally, wages are also a key control variable in our estimation. However, we do not observe equivalent wage payments to the owner, which are a substantial fraction of the true labor costs. To surmount this issue, we instead impute a firm-level wage rate using labor expenses that are reported in the KFS. To construct our imputed wage rate, we first divide the total labor expenses by the number of full-time equivalent employees to obtain a wage rate for each firm that reports labor expenses and satisfies our sample inclusion criteria. Next, we estimate the average wage rate for Black- and White-owned firms separately. Then, we multiply the race-specific average wage rate by the total number of owner-operators to obtain total imputed owners' compensation. Finally, we add up the owners' compensation with labor expenses, and divide by the total count of labor to obtain a firm-race-specific wage rate.

Table 1 provides some descriptive statistics of our sample, providing some general context regarding our sample for analysis.[8] We report statistics split by race, with about 6% of firms in our sample being classified as Black-owned. Columns 1 to 5 report various statistics of firms at the year of founding. In general, we see that upon entry, Black-owned firms earn about one-third of the revenue of White-owned firms, and own about half the assets of White-owned firms (Columns 1 to 2). These broad statistics have been similarly reported in prior research (e.g., Fairlie et al. (2020)); in particular, the disparity in asset holdings often forms the motivating fact of earlier research which argues that capital constraints are the primary barrier to growth of Black-owned firms. Interestingly, we see that there are not many differences between Black- and White-owned firms in terms of employment (Column 3); in fact, White-owned firms appear more likely to be non-employer firms relative to Black-owned firms. Taken together, we see that Black-owned firms generate lower revenue relative to assets, and also operate with lower capital intensity (Columns 4 to 5).

Columns 6 to 10 in turn report the same set of statistics for the full sample up to the

[8] More details on the KFS, as well as the criteria for sample inclusion into our analysis, are provided in Appendix B. For 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.

year 2011. We see that revenue generally doubles across the distribution, while capital is larger by about fifty percent (Columns 6 and 7). Interestingly, employment growth is more muted (Column 8). In turn, the average revenue relative to assets is lower, but the average ratio of assets to employment is higher (Columns 9 to 10).

3.2.1 Control variables $X_{i,t}$

As we noted, there are a number of potential confounding variables that could bias our estimates, with the key concern being that fundamental productivity or profitability is systematically correlated with race.

To address this issue, we always consider as a common set of control variables key characteristics of the primary owner, including (i) the number of years of prior relevant work experience (in logs), (ii) education (categorized in three groups: below college degree, some college degree, and some advanced degree), (iii) age (in logs), (iv) number of hours worked (in logs), (v) percentage of ownership, and (vi) gender (indicator variable for male or female). 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 control for productivity if the number of hours worked is increasing in the productivity of the firm; while the fifth variable helps us 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 possibility that firm profitability is associated with gender.[9]

Besides the control variables discussed above, we also additionally consider wealth as a control variable, due to the reasons discussed in Section 2.3. In the KFS, individuals are surveyed about their net worth, and given five options: negative; $0 to $50,000; $50,001 to $100,000; $100,001 to $250,000; above $250,000. In our specification, we consider wealth as

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

a categorical variable. However, because the wealth variable is only available for the year 2008 onward, we always consider a separate specification that includes wealth, on top of the baseline set of controls.

3.2.2 Why Control for Wages?

In principle, controlling for wages is unnecessary so long as individual-specific wages (i.e., $w_{i,t}$) are uncorrelated with race. However, much recent research has emphasized the possibility that Black- 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. Therefore, ignoring wages would bias us towards uncovering a capital wedge; likewise, it would reduce the statistical power of the capital-labor ratio in controlling for the capital and labor wedges in the first step of our estimation procedure.

4 Baseline Cross-Sectional Facts

In this section, we first report our baseline estimate for the markup and capital wedge using the framework presented in Section 2. Then, in the following subsections, we present extended analyses that examine the validity of our inference that the estimated coefficients of interest can be interpreted as racial discrimination.

4.1 Estimates of the Markup and Capital Wedge

We estimate the markup and capital wedges using seemingly unrelated regressions subject to cross-equation restrictions on δ^{μ}, δ^{r}, and δ^{l}.[10] Panels A and B of Table 2 report our estimates of the markup and capital wedges respectively. While not a focus of our paper, we also report our estimate of the labor wedge in Table A3 of Appendix E. In general, Column 1 reports our estimates without any control variables besides industry and year fixed effect to establish a reference value, Column 2 reports the estimates after including as control variables proxies for productivity (i.e., $X_{i,t}$), while Column 3 reports the estimates when wealth is additionally controlled for. However, the results in Column 3 are not comparable to those in Column 2, because the wealth variable is available only for the year 2008 onward. Therefore, in Column 4, we repeat our analysis using the post-2008 sample without controlling for wealth.[11]

4.1.1 Markup Wedge

Turning first to the markup wedge, we see that the markup wedge is -0.628 log points in the simplest specification (Column 1), and rises to -0.707 log points when we further control for productivity (Column 2). When we include wealth as an additional control variable, the markup wedge falls to -0.535 log points (Column 3); moreover, we find that this attenuation is not purely due to changes in sample (Column 4). Regardless, we find that all estimates are statistically significantly different from zero at conventional levels. At face value, this suggests that Black entrepreneurs face relatively lower consumer demand, which we attribute to consumer discrimination.

What is the economic significance of the markup wedge? Note that via Equation 4, one can interpret the markup wedge as the difference in the average return to capital relative to average capital user cost, i.e., the difference in average q after controlling for capital

[10] In terms of practical implementation, we estimate the equations using the reg3 command in Stata, and utilize the survey weights provided by the KFS. We also use robust standard errors.

[11] Note that while the majority of our analysis will focus on estimating averages in differences in markups and capital cost, we also conduct a statistical decomposition of the markup and capital wedges in Appendix E.I.

user costs. Using our most conservative estimate (i.e., Column 3), a back-of-the-envelope calculation implies that the average "market value" of White-owned firms is 1.71 times that of Black-owned firms.[12]

How does this result compare with estimates of the racial wealth gap, in particular, the racial gap in business wealth? Using data from the 2004 wave of the Survey of Consumer Finances, we find that the net value of White-owned businesses is approximately 2.83 times that of Black-owned businesses.[13] In other words, if we consider the firms in the KFS as representative of all private businesses in 2004, then our finding implies that about 60% of the racial gap in business wealth can be attributed to differences in the *market value* of their firms. In other words, a valuation gap between Black- and White-owned firms is the dominant driver of the racial gap in business wealth.

4.1.2 Capital Wedge

Turning next to the capital wedge, we see that the capital wedge is 0.23 log points in the simplest specification (Column 1), and rises to 0.26 log points when we further control for productivity (Column 2). Both estimates are statistically significant at conventional levels. At face value, this suggests that Black entrepreneurs face higher cost of capital, which we attribute in our context to financial discrimination.

However, when we include wealth as an additional control variable, the capital wedge is substantially attenuated, falling to 0.093 log points (Column 3). Moreover, the estimate is now statistically insignificant. Notably, this attenuation is not due to sample differences; in Column 4, we find that the capital wedge is almost identical to our estimate in Column 1.

Taken in totality, our results are consistent with earlier research showing that a race-based capital wedge exists between Black- and White-owned firms (e.g., Bento and Hwang (2022a)). Unlike the extant research, we find that the capital wedge appears to be "explained"—in a statistical sense—by the racial wealth gap. That is, Black-owned firms are relatively less

[12]To obtain our estimate, one simply computes $\frac{1}{exp(-0.535)} \approx 1.71$.

[13]See Table A2 of Appendix C.III.

capital intensive because Black entrepreneurs simply have less resources to begin with. That said, our estimates of the capital wedge are still sizable, economically speaking. For instance, as a concrete example, if White entrepreneurs face a market interest rate of 4%, a capital wedge of 0.093 log points implies the average Black firm faces an implied interest rate of 4.4%.[14]

4.2 Does δ^{μ} Identify Consumer Discrimination?

Our statistical analysis so far has identified a gap in profitability between Black- and White-owned firms, and attributed it to consumer discrimination. In the next six subsections, we provide a richer analysis to buttress our argument.

4.2.1 Black-owned firms with a higher dependence on international sales face a lower or no markup wedge

In this subsection, we exploit the fact that the context we are studying is primarily an American experience. In other words, the differences between Black and White communities are driven by a shared national experience, but not necessarily suffered across borders. We hypothesize that, if local racial animosity were the primary driver of the markup wedge, then Black-owned firms who primarily depend on international sales should face similar demand compared to White-owned firms who also sell overseas.

To that end, we explore two dimensions of the KFS to quantify the degree to which a firm depends on international sales. First, we exploit the fact that survey respondents are asked (from 2007 onwards) about the location of where the majority of the firm's customers are located. The survey provides respondents with five options, which we bin into two categories, "domestic" and "international". Second, survey respondents are also asked about the fraction of sales that are outside of the United States.[15]

[14] To obtain our estimate, one simply computes $4 \times exp(0.093) \approx 4.4$.

[15] The respondents are given a choice of (i) less than 5%, (ii) between 5% to 25%, (iii) 25% to 50%, (iv) 50% to 75%, and (v) 75% to 100%. In our estimation, we simply aggregate up options (i) and (ii) as a single category to create equally-spaced bins, with the lowest bin (=1) indicating firms that report the lowest

To test our hypothesis, we estimate Equation 11. This equation is similar to our baseline specification (i.e., Equation 7), with the exception that we also allow for an interaction term between the Black indicator function and a variable ($INTL$) indicating the degree to which a given firm is classified as being more dependent on international sales. Like δ, both ι and ν are vectors and we estimate the system of equations restricting their entries to be identical. Our hypothesis is that $\nu > 0$, indicating that Black-owned firms which sell overseas have a lower markup wedge.

$$\log y_{i,j,t} = \alpha + \delta \times \mathcal{I}_{black} + \varsigma \log \left(\frac{k}{l}\right)_{i,t} + \eta \log w_{i,t} + \iota \times INTL ...$$
$$... + \nu \times \mathcal{I}_{black} \times INTL + X'_{i,t}\beta + \gamma_j + \theta_t + u_{it}. \tag{11}$$

We operationalize this estimation in two ways. First, we define $INTL$ as an indicator function, evaluating to 1 if the firm is classified as "international" per our earlier description. Panel A of Table 3 reports our estimation results per this definition, with regression specifications mirroring their counterparts in Table 2. As we can see, ν is always larger than 0 and statistically significant. Moreover, for Columns 2 to 4, we find that $\delta + \nu$ is statistically not different from zero; in other words, Black firms who are primarily selling overseas do not suffer a markup wedge.

Second, we define $INTL$ as a *continuous* variable using the second variable as described above. While this strategy is not ideal, it allows us to maximize the degree of freedom given our small sample size. Importantly, this definition does not affect our qualitative inference. Panel B of Table 3 reports our estimation results per this definition, where we again see that ν is always larger than 0 and statistically significant.

amount of international sales.

4.2.2 Black-owned firms with a higher dependence on government procurement face a lower markup wedge

We posit that the government, as a consumer, would be less likely to be discriminatory relative to private consumers, given the relatively stricter standards to which governmental agencies are held. Moreover, as we alluded to in our introduction, some levels of government (such as the federal government) are actively providing procurement opportunities to promote minority businesses. As such, it seems unlikely that the same agency would also simultaneously be discriminatory. In this context, we hypothesize that, if racial animosity were the primary driver of the markup wedge, then Black firms who primarily depend on business-to-government (B2G) sales should face a smaller markup wedge compared to otherwise identical White firms.

We approach this hypothesis in two ways. First, we exploit another dimension of the KFS to quantify the degree to which a firm depends on government procurement. Specifically, respondents are asked to approximate the share of sales that accrue from sales to consumers, businesses, and governmental agencies. We define a firm as B2G if sales to government agencies form the majority of the firm's sales.

To test our hypothesis, we estimate Equation 12. This equation is similar to our baseline, but we now include an interaction term between the Black indicator function and an indicator variable ($B2G$), which evaluates to 1 if the firm is classified as B2G, and 0 otherwise. Our hypothesis is that $\nu > 0$, indicating that Black-owned firms which are primarily B2G should face a lower markup wedge.

$$\log ARPK_{i,j,t} = \alpha + \delta \times \mathcal{I}_{black} + \iota \times B2G + \nu \times \mathcal{I}_{black} \times B2G + ...$$
$$...X'_{i,t}\beta + \gamma_j + \theta_t + u_{it}. \tag{12}$$

Our results are reported in Panel A of Table 4. We see that ν is always larger than 0 and statistically significant. Moreover, from the estimates, we see that being a B2G firm approximately reduces the markup wedge by half.

Second, we further explore the role of federal procurement by merging in additional data on U.S. federal contracting expenditure for the years 2004 to 2011.[16] Specifically, we observe the dollar value of a federal contract for a given firm at a given year, the location of the firm at the county level, and whether the firm is classified as a "Black-owned" firm. While we cannot directly map the procurement data to the firms in the KFS due to confidentiality reasons, we do observe the location of the firm at the county level. Therefore, we aggregate up total federal procurement expenditure, and separately, total procurement expenditure directed towards Black-owned firms, at the county-year level. Then, we construct the share of federal procurement directed towards Black-owned firms, and merge this panel of county-year observations back into the KFS.

We postulate that, holding fixed the total size of federal procurement, Black-owned firms operating in counties with a larger share of federal procurement directed towards Black-owned firms should face a lower markup wedge. To operationalize this, we estimate Equation 13. This specification is similar to Equation 12 with two key differences: For a given county c at year t, (i) we replace the binary $B2G$ variable with a continuous variable in the form of the share of federal procurement expenditure directed towards Black firms ($ShareBlackProcure_{c,t}$, implemented in fractions), and (ii) we additionally control for the (log) total amount of federal procurement ($logProcure_{c,t}$). Like with the earlier specification, our hypothesis is that $\nu > 0$.

$$\begin{aligned}\log ARPK_{i,j,c,t} = \alpha + \delta \times \mathcal{I}_{black} + \iota \times ShareBlackProcure_{c,t} ... \\ ... + \nu \times \mathcal{I}_{black} \times ShareBlackProcure_{c,t} + \psi \times logProcure_{c,t} ... \\ ... + \phi \times \mathcal{I}_{black} \times logProcure_{c,t} + X'_{i,t}\beta + \gamma_j + \theta_t + u_{it}. \qquad (13)\end{aligned}$$

Our results are reported in Panel B of Table 4. For our estimation, we only utilize

[16] The data can be accessed from https://www.usaspending.gov. Descriptive statistics for this auxiliary data along with more detailed instructions for accessing the data, is provided for in Appendix C.I.

observations for which $ShareBlackProcure_{c,t} > 0$. In general, we see that ν is always larger than 0, and statistically insignificant only for the first specification without any control variables.[17]

4.2.3 Black-owned firms operating in counties with a larger Black population share face a lower markup wedge

We further postulate that, if local racial animosity were a driver of the markup wedge, then Black-owned firms that operate in counties with a higher proportion of Black individuals (relative to White individuals) would face a lower markup wedge, since the severity of a demand deficit would be smaller.

To explore this hypothesis, we bring in population data from the Current Population Survey (CPS). We use the CPS to construct county-level annual data of the population count of Black and White individuals, then further compute the share of Black individuals relative to total individuals. Then, we merge this county-year panel back into the KFS.

With the merged data, we then estimate Equation 14, where $ShareBlackPop$ refers to the fraction of the population in a given county and year who are Black. Our hypothesis implies that $\nu > 0$.

$$\log y_{i,j,c,t} = \alpha + \delta \times \mathcal{I}_{black} + \iota \times ShareBlackPop_{c,t} + ...$$
$$...\nu \times \mathcal{I}_{black} \times ShareBlackPop_{c,t} + X'_{i,t}\beta + \gamma_j + \theta_t + u_{it}. \quad (14)$$

Our results are reported in Table 5, where we see that ν is statistically significantly larger than 0.

[17] If government procurement contracts are in part directed towards relatively more disenfranchised demographics, then we would expect to see an attenuation of ν without control variables.

4.2.4 Black-owned firms operating in counties with a smaller proportion of Republican voters face a lower markup wedge

We now explore the dependence of the markup wedge on local political interest. Recent research (e.g., Kuziemko and Washington (2018)) has shown that support for Black voters' political interest is less concentrated in the Republican Party than the Democratic Party. Consequently, to the extent that racial animosity is the driver of the markup wedge, we would expect to see a larger markup wedge in locations where there are relatively more Republican voters.

To that end, we borrow the approach of Aneja, Luca, and Reshef (2023) by merging in precinct-level voting data for the 2004 presidential election in the United States (Data and Lab (2018)). Specifically, we aggregate the vote count for each party to the county level, compute the vote share for the Republican Party in each county, then merge this data back in to the KFS. We then estimate a regression specification of the form given by Equation 15, where the variable $RepublicanShare_c$ quantifies the degree to which a given county leans Republican.

$$\log y_{i,j,c,t} = \alpha + \delta \times \mathcal{I}_{black} + \iota \times RepublicanShare_c + ...$$
$$...\nu \times \mathcal{I}_{black} \times RepublicanShare_c + X'_{i,t}\beta + \gamma_j + \theta_t + u_{it}. \tag{15}$$

We operationalize this estimation in two ways. First, we define $RepublicanShare$ as an indicator function, evaluating to 1 if a county reports a majority Republican vote share. This follows the approach of Aneja et al. (2023). Second, we define $RepublicanShare$ as a continuous variable, namely, the fraction of votes that accrue to the Republican Party. In both cases, our hypothesis is that $\nu < 0$.

We report our results in Table 6, where Panel A reports the results with $RepublicanShare$ as a binary variable, and Panel B reports the results with a continuous variable. In all results, we see that $\nu < 0$, and is statistically significant at conventional levels.

4.2.5 Counter-hypothesis: 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, as we discussed earlier in Section 2.3. 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 the customers of Black-owned firms simply have lower disposable income.

A challenge in addressing this counter-hypothesis is that we simply do not observe the customer base (and their demographics) of each firm, and therefore cannot simply control for the income of their customers. To surmount this challenge, we instead address this issue in two different ways.

Exploiting geographical differences in income Building on the idea that the majority of firms in the KFS have a customer base that is located within a close geographical region, we merge in county-level income data from the CPS. Specifically, we compute, for each county and year, the average income of Black and White households. Then, we sequentially include the log of the average income of Black and White households into our regression as control variables; where the inclusion of the income of Black households directly addresses the issue that Black consumers have lower disposable income, while the inclusion of the income of White households additionally addresses the issue that Black-owned firms might be operating in lower income neighborhoods.

Panel A of Table 7 reports the estimation results controlling for the income of the Black population, while Panel B reports the estimation results and further controls for the income of the White population.

Comparing the results with Table 2, we see that estimates of the markup wedge are smaller but relatively similar, and importantly, continue to be statistically significantly different from 0. In other words, there is some evidence that the markup wedge is associated with the average income of the typical customer of a Black-owned firm, but that association is not the dominant driver.

Exploiting product homogeneity differences We next exploit the idea that pure consumer discrimination should generate a larger profitability gap in industries in which 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 directly affected by racial discrimination, since they have a captured consumer base. A key assumption here is that Black consumers shopping in either market have the same average income.

To test our hypothesis, we estimate Equation 16 below, where $\mathcal{I}_{homog}$ is an indicator function that evaluates to 1 when the sector the business is in produces a homogeneous good, and 0 otherwise. For our purposes, we classify any firms that operate in the construction or manufacturing sector as producing a relatively homogeneous good, whereas we regard firms operating in services and retail trade as producing a relatively less homogeneous one.[18] Therefore, our hypothesis, if true, would imply that $\nu < 0$; that is, Black-owned firms in more homogeneous industries face a larger markup wedge.

$$\log y_{i,j,t} = \alpha + \delta \times \mathcal{I}_{black} + \iota \times \mathcal{I}_{homog} + \nu \times \mathcal{I}_{black} \times \mathcal{I}_{homog} + ...$$
$$...X'_{i,t}\beta + \gamma_j + \theta_t + u_{it}. \tag{16}$$

We report our results in Panel C of Table 7. As we can see, the coefficient ν is always statistically significant and negative.

[18] While admittedly crude, we believe our classification is reasonable and sufficient for our qualitative analysis. For instance, 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. In Appendix E.II, we present a placebo test providing support for our classification choices.

4.2.6 Counter-hypothesis: Can Productivity Differences Explain the Markup Wedge?

We finally 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 specifications, but focusing on two specific subsets of firms: Firms that are run by owners who have an advanced degree, and firms that are incorporated (S-Corp/LLC). Our 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 Columns 1 and 2 of Table 8. For comparability, we first report results for our baseline without any other controls (Panel A), our specification with controls (Panel B), and our last specification, which also includes wealth as a control (Panel C). We find that, by and large, the difference in average markups between Black- and White-owned firms is similar to the full sample.

Selection Effects Due to Labor Market Frictions A related argument is that labor market frictions for Black individuals might force lower-productivity Black individuals to pursue entrepreneurship out of necessity. Such negative selection can also drive down revenue productivity, making it appear that Black entrepreneurs face consumer discrimination.

However, we do not believe this to be a dominant force in the economy. Importantly, negative selection generally implies that Black entrepreneurs should be over-represented in the economy. In contrast, as we report in Table 1, 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.

4.3 Does the Capital Wedge Identify Credit Discrimination?

Our statistical analysis has also identified a gap in implicit capital costs between Black- and White-owned firms, and attributed it to credit discrimination. While we find that wealth attenuates somewhat the statistical relevance of the capital wedge, our point estimate suggests a continued presence of the capital cost wedge. We now explore further whether other differences between Black and White entrepreneurs can explain this gap.

4.3.1 Exploring the role of risk

While our framework abstracts away from uncertainty, we now explore the possibility that the capital cost wedge arises because Black-owned firms are simply riskier than White-owned firms. Differences in risk premia can impact financing in two key ways, both of which would generate a capital cost wedge. First, Black entrepreneurs might simply demand less credit due to risk aversion, implying that the capital cost wedge is not a result of discrimination. Second, financial lenders could reduce their supply of credit to Black startups due to statistical discrimination (Bostic and Lampani (1999), Blanchflower, Levine, and Zimmerman (2003), Cavalluzzo and Wolken (2005), Blanchard, Zhao, and Yinger (2008), Bates and Robb (2016), Bates, Bradford, and Jackson (2018)). Since startups do not have an established track record, financial lenders might attempt to infer their riskiness on the basis of the race of the owner. While ostensibly innocuous, we note that this behavior is a form of racial discrimination and unlawful in the United States.[19]

We proxy for the riskiness of firms using four "ex post" measures, that is, risk characteristics observable only *after* the formation of the startup. The first three are direct measures of credit risks as reported in the KFS and computed by Dun and Bradstreet. The first comes from the firms' commercial credit score, as binned into five categories, with a bin of 1 indicating firms with the highest risk. The next two are computed by Dun and Bradstreet. The *PAYDEX* score reports the timeliness of a company in repayment, where a lower 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 12 months, with an emphasis on business failure. Both measures are also decreasing in risk. Finally, because the first three measures are computed by an external agency and might not be objective or accurately capture economic risk, 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)). Our construction of returns on assets (ROA) follows Morazzoni and Sy (2022), who utilize the same data set as our paper. In Panel A of Table 9, we show that Black businesses do indeed exhibit riskier characteristics, even after we control for observable covariates and wealth as before. For instance, Black-owned firms have lower credit scores and higher volatility.

With these measures in hand, we next separately include these measures as additional control variables in our estimating equation. The results are reported in Columns 5 to 8 of Table 9. As hypothesized, we see that the inclusion of a risk control generally attenuates our point estimate of the impact of race, where this attenuation ranges from around 21% (vol. ROA) to 58% (*PAYDEX*). As such, this suggests that there is evidence that our estimated capital wedge reflects risk differences between Black- and White-owned firms.

[19]Specifically, the Equal Credit Opportunity Act (ECOA) makes it illegal for a creditor to discriminate in any aspect of credit transaction, including extensions of credit to small businesses, corporations, partnerships, and trusts based on certain characteristics (e.g., race, color, religion, sex, etc.). For more details go to www.consumerfinance.gov.

4.3.2 Exploring the role of expected profitability

As we discussed in Section 2.3, Black-owned firms might simply have lower expected profitability; in this case, financial lenders would be less willing to extend credit. We explore this hypothesis using the same strategy as earlier in subsection 4.2.6, by re-running our baseline regression specification on the subset of firms that are incorporated and the subset of firms run by owners with an advanced degree.

Columns 3 to 4 of Table 8 summarizes our results, showing that for incorporated firms, the capital wedge is attenuated but still statistically significant (Column 4). In contrast, for the subset with an advanced degree (Column 3), the point estimate is *negative*, implying at face value a credit subsidy for Black-owned firms run by entrepreneurs with an advanced degree. However, the estimate is statistically insignificant. Taken in totality, there appears evidence that the capital wedge we uncovered might also be reflective of expectations of lower expected profitability by financial lenders.

4.4 Are the Markup and Capital Wedges Heterogeneous?

Our estimation strategy so far relies on OLS, which allows us to uncover the average markup and capital wedges. However, this analysis hides potential heterogeneity across the distribution.

First, our basic model assumes that the markup wedge is constant across the distribution of d_i. This implies that a high-productivity Black-owned firm faces the same degree of disadvantage as a low-productivity Black-owned firm, implying that they all face the same barriers to growth.

However, it is plausible that the markup wedge is varying in productivity. To analyze this dimension of heterogeneity, we estimate Equation 7 using a quantile regression with our full set of controls $X_{i,t}$. Results are reported in Panel A of Figure 1, which plots the coefficients of the quantile regressions at each decile, from 10th to the 90th percentiles. Contrary to our hypothesis, we see that the markup wedge is relatively flat in productivity, although it appears to be decreasing past the 70th percentile.

We also explore whether the capital wedge is heterogeneous. In practice, individuals can face different cost of capital due to a multitude of differences such as wealth or risk characteristics, giving rise to a distribution in r_i. Our baseline model assumes that the capital wedge is constant across r_i; we now investigate whether the capital wedge is heterogeneous across the distribution of r_i.

To that end, we compute markup-adjusted ARPK using Equation 8 for each decile of the markup wedge. Then, for each corresponding decile, we estimate the capital wedge using quantile regression. Panel B of Figure 1 plots the coefficients of the quantile regressions from 10th to the 90th percentiles. Here, we see that the capital wedge is increasing in r_i. This implies, for instance, that wealthier Black entrepreneurs face a smaller capital wedge than less wealthy Black entrepreneurs.

4.5 Robustness Analysis Using the Survey of Small Business Finances

As a complementary robustness check of our main results, we also draw on data from the Survey of Small Business Finances (SSBF) and re-conduct our baseline analysis. The SSBF is similar to the KFS in that it provides detailed information on small businesses in the United States, but is designed to provide cross-sectional information from a nationally representative sample. Appendix C.IV summarizes the survey structure of the SSBF, and provides more details on how we construct our variables of interest. The main point of this exercise is to emphasize that our results are not unique to the KFS.

Estimates of the markup and capital wedges are reported in Appendix D.II.2, where Tables A4 to A6 report results from survey waves of 1993, 1998, and 2003. The tables are arranged to be aligned in the same way as Table 2. Broadly speaking, we find that estimates for the markup wedge using the SSBF align quite well with the estimates from the KFS, but we find that the capital wedge estimates align less well with the KFS. While we uncover a point estimate that implies a positive capital wedge, the estimate is sometimes statistically insignificant. We believe this difference arises because the capital wedge appears transient over the life cycle of the firm (as we report in Section 5); since the SSBF is drawn from the full distribution of entrepreneurs, our estimates of the capital wedge would become more attenuated relative to the KFS.

5 Which Matters More? Credit Supply or Customer Demand?

We showed earlier that Black-owned firms face both lower customer demand and tighter credit supply. 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.

5.1 Empirical Strategy

Our empirical strategy borrows insights from the macroeconomic literature arguing that credit constraints do not generate persistent differences across firms, since firms can accumulate liquidity to the point that credit constraints are no longer binding (e.g., Moll (2014)). In our context, this implies that the capital cost wedge should fade out over time as Black entrepreneurs accumulate sufficient wealth to negate the constraints on credit supply.

In contrast, demand 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.

We therefore hypothesize that over the life cycle of the firm, customer demand differences would matter more than credit supply differences. 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 convergence in capital cost 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 re-estimate the markup and capital wedges year-by-year, giving us year-specific estimates of δ^{μ} and δ^{r}. For our specification, we control for all covariates mentioned in the earlier section, without accounting for wealth, owing to our sample limitations.

5.2 Main Results

5.2.1 Markup Differences Are Persistent

We first present our findings of the dynamics of the markup wedge, which we report in Panel A of Figure 2. Each point of the plot refers to an estimate of the markup wedge for the year. Looking to the general time series, we find that the markup wedge is relatively consistent across all years. This matches our hypothesis that consumer discrimination generates a persistent markup wedge, since Black entrepreneurs cannot unilaterally address this issue.

5.2.2 Capital Cost Differences Are Partly Transient

Next, we present our findings for the capital wedge, which we report in Panel B of Figure 2. Our analysis unveils two key findings. Looking to the first half of the sample, which goes up to year 2008, we see a rapid reduction in the capital 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 to overcome their financial constraints over time, and at a relatively fast rate.

However, looking to the second half of the sample, we see a re-emergence of the capital wedge: Between 2008 and 2009, the capital wedge rises almost back to its initial levels. As is well known, a sharp financial crisis occurred in 2008, during which credit supply was substantially restricted. Our finding suggests that in the wake of the Great Recession, credit was disproportionately rationed from Black-owned firms. 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 obviously impeded by credit supply constraints during the growth phase of the firm. Our finding mirrors recent research by Fairlie et al. (2020) using the same KFS data, but with a key difference. Unlike them, we emphasize a rapid reduction in the *capital cost wedge*, whereas Fairlie et al. (2020) 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 because of 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 regard to credit constraints, as revealed by a rapid reduction of the capital wedge.[20]

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 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. This suggests that demand-side factors appear to be a relatively more important barrier to the equalization of entrepreneurial opportunity.

[20]While we argue that the reduction in the capital wedge is driven by self-accumulation of assets, a threat to our argument is the possibility of survivorship bias. We address this issue in more detail in Appendix E.IV. Our extended analysis suggests that survivorship bias is unlikely to be an issue, although it is not something we can definitively rule out.

However, such a conclusion includes two caveats. First, the re-emergence of a capital wedge after the financial crisis implies that self-accumulation is not a sufficient buffer stock for Black-owned firms, and unexpected aggregate shocks more severely impact Black-owned firms. Second, and more importantly, the capital wedge only identifies the degree to which credit supply is constraining to Black entrepreneurs. Because we identify such a large gap in consumer demand, it is probable that race-based credit constraints are not severely constraining due simply to lower credit demand in the first place. In contrast, equalization of demand might lead to a much larger and more persistent capital wedge.

5.3 Markup Wedge and Initial Conditions in Financing

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 has emphasized the importance of growing intangible assets such as 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 disadvantage in expanding their stock of intangible assets, then Black entrepreneurs might face lower demand due simply to their initial financial conditions.

To address this, we subset White-owned firms into two groups: a set of firms below a cut-off in capital intensity such that they have approximately no capital wedge relative to Black-owned firms at *startup*, and a complement set above the same cut-off. We find approximately 75% of White-owned firms fall below this threshold. Then, we re-estimate the markup wedge year-by-year for each of these subsets of White-owned firms. If differences in initial conditions regarding financing are the dominant driver of the markup wedge, we should find a zero (or small) markup wedge between the Black- and White-owned firms for which there is no capital wedge at founding.

Our results are reported in Figure A2 (Appendix E.III). In summary, we find that a markup wedge is a persistent feature in both sub-samples. However, we also find that the gap in markups, at the initial year of founding, is almost 50% larger when comparing Black-owned firms with the subset of White-owned firms with a positive capital wedge, relative to the complement subset without a capital wedge, and that these differences are statistically significant. Furthermore, the differences in the markup wedge narrow over the course of the years when the capital wedge disappears, and become statistically indifferent from each other. Taken in totality, our results suggest there is some evidence that differences in initial financial conditions could be a driver of the markup wedge; however, they are unlikely to be the dominant driver.

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 those of White-owned firms, which we interpret as consumer and credit discrimination. However, we also find that credit constraints alone do not appear to 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. Moreover, a substantial degree of the capital supply differences appear to be explained by racial differences in wealth and business risk. In contrast, consumer demand differences are insurmountable by Black individuals alone, and are robust to multiple competing hypotheses.

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 aimed at reducing credit costs for Black-owned firms, but little emphasis has been 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, we argue that the large racial wealth gap would not be a persistent fact over generations if credit discrimination was the only barrier. In contrast, persistent consumer 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, as is primarily practiced today, while important in promoting the entry of under-capitalized Black businesses, are 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

Table 1: Summary Statistics

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

	% of Sample	Percentile	On Founding					Full Sample				
			Revenue ($)	Non-cash assets ($)	Empl (#)	$\frac{Rev}{Assets}$	$\frac{Assets}{Empl}$	Revenue ($)	Non-cash assets ($)	Empl (#)	$\frac{Rev}{Assets}$	$\frac{Assets}{Empl}$
			(1)	(2)	(3)	(4)	(5)	(6)	(7) ($)	(8)	(9)	(10)
White	94%	25	16,832	7,468	0	1.08	3,293	31,653	12,619	0	0.96	5,252
		50	60,594	28,053	0	3.63	9,585	113,910	46,721	1	3.19	16,411
		75	168,316	97,258	2	10.27	29,216	410,931	170,866	4	7.91	45,107
Black	6%	25	5,611	4,067	0	0.58	1,325	10,871	6,500	0	0.58	2,813
		50	22,442	11,592	1	4.13	4,488	38,717	24,590	1	2.46	8,053
		75	84,158	49,968	3	7.61	14,026	140,263	86,999	3	6.40	26,684

Table 2: Baseline Estimates of the Markup and Capital Wedges

	(1)	(2)	(3)	(4)
		Panel A: Markup Wedge		
δ^{μ}	-0.628	-0.707	-0.535	-0.672
	(0.073)	(0.063)	(0.084)	(0.088)
Observations	8832	8553	4399	4399
R^2	0.372	0.518	0.554	0.528
		Panel B: Capital Wedge		
δ^{r}	0.226	0.263	0.093	0.214
	(0.090)	(0.085)	(0.115)	(0.117)
Observations	8832	8553	4399	4399
R^2	0.135	0.162	0.208	0.161
Controls	No	X	X, wealth	X, 2008+

Notes: This table reports our estimates for the markup and capital wedges. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Table 3: Dependence on international sales and the markup wedge

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: As binary				Panel B: As "continuous"			
δ	-0.709	-0.731	-0.552	-0.700	-1.304	-1.288	-1.279	-1.422
	(0.088)	(0.076)	(0.087)	(0.090)	(0.261)	(0.230)	(0.241)	(0.268)
ν	1.074	0.640	0.384	0.665	2.862	2.219	1.940	2.358
	(0.226)	(0.201)	(0.210)	(0.218)	(0.510)	(0.432)	(0.450)	(0.479)
Controls	No	X	X, wealth	X, 2008+	No	X	X, wealth	X, 2008+
Observations	5949	5713	4370	4370	1084	1026	799	799
R^2	0.375	0.521	0.552	0.525	0.347	0.453	0.509	0.481

Notes: This table reports our estimation results per Equation 11, where the estimates of interest are δ and ν. All other coefficients are suppressed for the sake of brevity. Panel A reports results when we consider dependence on international sales as a binary variable, and Panel B reports results associated when we consider dependence as a continuous variable. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Table 4: Dependence on government procurement and the markup wedge

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: B2G from KFS				Panel B: Procurement			
δ	-0.714	-0.760	-0.603	-0.758	-0.754	-0.398	-1.422	-1.154
	(0.078)	(0.068)	(0.095)	(0.098)	(0.584)	(0.530)	(0.684)	(0.733)
ν	0.640	0.368	0.314	0.418	1.121	2.072	2.706	2.779
	(0.178)	(0.170)	(0.153)	(0.178)	(1.011)	(0.854)	(1.027)	(1.063)
Controls	No	X	X, wealth	X, 2008+	No	X	X, wealth	X, 2008+
Observations	8832	8553	4399	4399	8772	8493	8772	4365
R^2	0.374	0.519	0.555	0.529	0.375	0.517	0.554	0.527

Notes: This table reports our estimation results per Equation 12, where the estimates of interest are δ and ν. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Table 5: Black population share and the markup wedge

	(1)	(2)	(3)	(4)
δ	-0.947	-0.986	-0.732	-0.899
	(0.130)	(0.115)	(0.153)	(0.161)
ν	1.012	1.008	0.810	0.931
	(0.440)	(0.413)	(0.475)	(0.521)
Controls	No	X	X, wealth	X, 2008+
Observations	8819	8540	4392	4392
R^2	0.374	0.518	0.554	0.527

Notes: This table reports our estimation results per Equation 14, where the estimates of interest are δ and ν. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Table 6: Republican vote share and the markup wedge

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Republican Majority				Panel B: Republican Vote Share			
δ	-0.420	-0.572	-0.416	-0.552	-0.138	-0.445	-0.193	-0.367
	(0.096)	(0.085)	(0.114)	(0.121)	(0.194)	(0.176)	(0.209)	(0.227)
ν	-0.552	-0.350	-0.320	-0.320	-1.183	-0.628	-0.797	-0.721
	(0.152)	(0.133)	(0.172)	(0.181)	(0.421)	(0.376)	(0.445)	(0.479)
Controls	No	X	X, wealth	X, 2008+	No	X	X, wealth	X, 2008+
Observations	8819	8540	4392	4392	8819	8540	4392	4392
R^2	0.3740	0.5180	0.5544	0.5276	0.373	0.518	0.554	0.527

Notes: This table reports our estimation results per Equation 15, where the estimates of interest are δ and ν. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Table 7: How much does market segmentation matter?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Control for income (Black)				Panel B: Control for income (All)				Panel C: Homogenous goods			
δ^{μ}	-0.598	-0.649	-0.460	-0.547	-0.567	-0.624	-0.413	-0.499	-0.444	-0.517	-0.314	-0.429
	(0.104)	(0.090)	(0.117)	(0.125)	(0.106)	(0.093)	(0.121)	(0.130)	(0.086)	(0.079)	(0.096)	(0.101)
ν									-0.625	-0.565	-0.693	-0.625
									(0.255)	(0.224)	(0.229)	(0.247)
Observations	2781	2697	1395	1395	2781	2697	1395	1395	6730	6504	3299	3299
R^2	0.368	0.543	0.605	0.573	0.373	0.548	0.612	0.581	0.303	0.463	0.503	0.474

Notes: This table reports our estimation results discussed in Section 4.2.5. Panel A reports results associated with the markup wedge, and Panel B reports results associated with the capital cost wedge. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Table 8: How much does controlling for productivity matter?

	Markup wedge		Capital wedge	
	Advanced degree	S-Corp/LLC	Advanced degree	S-Corp/LLC
	(1)	(2)	(3)	(4)
	Panel A: No Controls			
δ	-0.581	-0.548	-0.163	0.221
	(0.145)	(0.084)	(0.186)	(0.117)
Observations	1942	5441	1942	5441
R^2	0.401	0.506	0.158	0.151
	Panel B: Controls			
δ	-0.724	-0.568	-0.185	0.246
	(0.122)	(0.074)	(0.180)	(0.112)
Observations	1939	5273	1939	5273
R^2	0.601	0.587	0.196	0.164
	Panel C: Controls + Wealth			
δ	-0.720	-0.499	-0.267	0.022
	(0.142)	(0.118)	(0.234)	(0.159)
Observations	1029	2750	1029	2750
R^2	0.652	0.612	0.250	0.192

Notes: This table reports our estimation results for the markup wedge (Columns 1 to 2) and the capital wedge (Columns 3 to 4), for different subset of the sample, where the estimate of interest is δ. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

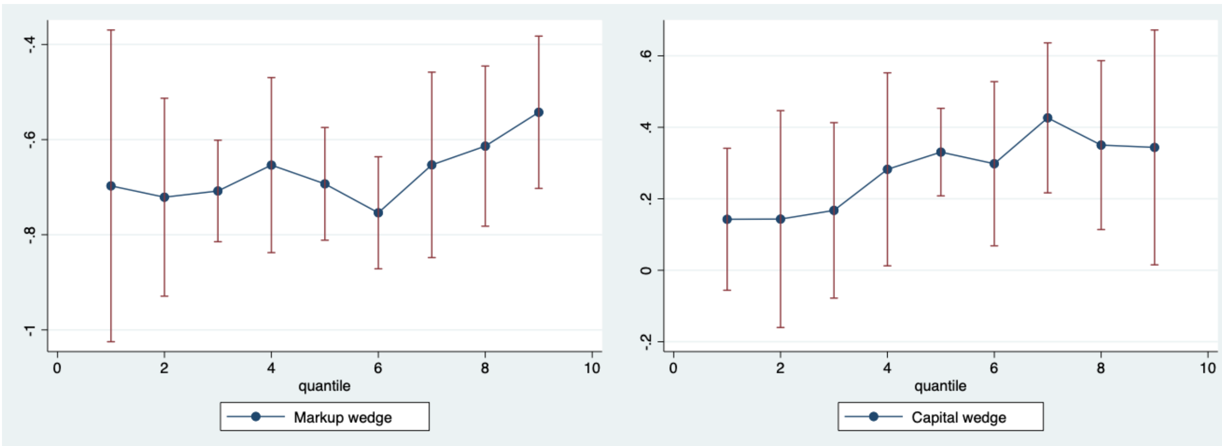
Table 9: Risk, race, and capital wedge

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Credit score	PAYDEX	FSSP	vol(ROA)	Credit score	PAYDEX	FSSP	vol(ROA)
	Panel A: Corr of race with risk				Panel B: Capital Wedge and risk			
ρ	-0.506	-0.217	-0.407	0.127				
	(0.062)	(0.055)	(0.078)	(0.043)				
δ^r					0.165	0.111	0.176	0.207
					(0.102)	(0.133)	(0.097)	(0.085)
Controls	X	X	X	X	X	X	X	X
Observations	7624	3779	7750	8595	7591	7717	3766	8553
R^2	0.080	0.039	0.061	0.092	0.179	0.172	0.144	0.232

Notes: Panel A reports the correlation of race with each listed risk measure with race, and Panel B reports estimates of the capital cost wedge controlling for each listed risk measure. All other coefficients are suppressed for the sake of brevity. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Figure 1: Distribution of the markup and capital wedge.

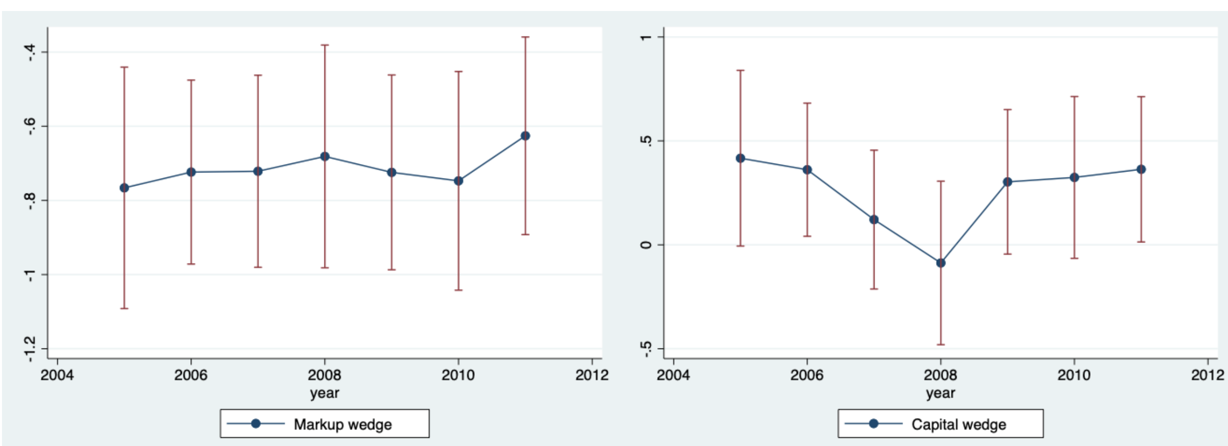
(a) Markup wedge. **(b)** Capital wedge.



Notes: Panel A reports the estimates of the markup wedge at each decile of ARPK, from the 10th to 90th percentile. Panel B reports the estimates of the capital wedge at each decile of markup-adjusted ARPK, from the 10th to 90th percentile. Error bars are 95% confidence intervals, computed using robust standard errors accounting for sample weights.

Figure 2: Markup and capital wedge over time.

(a) Markup wedge. **(b)** Capital wedge.



Notes: This figure plots the year-by-year markup (Panel A) and capital (Panel B) wedges. Error bars are 95% confidence intervals, computed using robust standard errors accounting for sample weights.

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Appendices

A Proofs and Derivations

In this section, we will expand on the derivations and proofs that lead up to Lemma 1.

A.I Proof of Corollary 1

For a generic demand function satisfying Assumption 1, all profit-maximizing firms set marginal revenue equal marginal cost. Denote by ϵ_p^W and ϵ_p^B the price elasticity that White and Black firms face in setting their optimal prices, and P^W and P^B the corresponding prices. Because both groups face the same marginal cost curve by Assumption 3 (specifically, marginal cost is constant since output features constant returns), the following equation must hold in equilibrium:

$$P^W \left(\frac{\epsilon_p^W - 1}{\epsilon_p^W} \right) = P^B \left(\frac{\epsilon_p^B - 1}{\epsilon_p^B} \right) \tag{17}$$

Next, by Assumption 2, we see that $\epsilon_p^W < \epsilon_p^B$ if $\tau_B^d - \tau_W^d < 0$. This implies that $\frac{\epsilon_p^W - 1}{\epsilon_p^W} < \frac{\epsilon_p^B - 1}{\epsilon_p^B}$. For equation 17 to hold, and given our assumption that the demand elasticity increases with prices, this means that $P^W > P^B$.

A.II Derivations of Equations 2 to 6

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

$$MRPK \equiv \frac{\partial p(y, d, \tau_g^d)y}{\partial k} = (1 + \tau_g^r)r, \tag{18}$$

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 4, note that MRPK can be rewritten as

$$\frac{\partial p(y, d, \tau_g^d)y}{\partial k} = \frac{\partial p}{\partial y}\frac{\partial y}{\partial k}y + \frac{\partial y}{\partial k}p \tag{19}$$

$$= \frac{\partial y}{\partial k}\left(\frac{\partial p}{\partial y}y + p\right). \tag{20}$$

Next, keeping in mind that

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

the ratio of MRPK to ARPK is given by

$$\frac{MRPK}{ARPK} = \frac{\partial y/\partial k}{y/k}\left(\frac{\partial p/\partial y}{p/y} + 1\right), \tag{21}$$

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 4 in the main text.

An identical derviation for labor gives us a similar expression for the marginal product of labor:

$$\frac{\partial p(y,d,\tau_g^d)y}{\partial l} = \frac{\partial y}{\partial l}\left(\frac{\partial p}{\partial y}y + p\right) = w, \tag{22}$$

which, like the derivation for MRPK, arranges to

$$ARPL = \frac{1}{\epsilon_l}(1+\mu)\, MRPL.$$

Taking logs, we obtain Equation 5 in the main text.

For Equation 6, we divide Equation 2 by 3 (and with slight abuse of notation), we obtain

$$\frac{\partial l/\partial k}{l/k}\frac{l}{k} = \frac{(1+\tau_g^r)r}{w}, \tag{23}$$

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, with a slight rearrangement of terms, gives us Equation 6.

A.III Proof of Lemma 1

To prove this, we simply need to invoke our assumption that physical production is CES. Standard cost minimization implies that

$$\frac{k}{l} = \left(\frac{\alpha}{1-\alpha}\frac{\left(1+\tau_g^l\right)w}{\left(1+\tau_g^r\right)r}\right)^{\eta}, \tag{24}$$

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, τ_g^r, and τ_g^l. In turn, this implies that $\epsilon_{k,l}$ is also trivially a function of r, w, τ_g^r, and τ_g^l.

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

$$\begin{aligned} \epsilon_k &= \alpha \left(\frac{y}{k}\right)^{\frac{\eta-1}{\eta}} \\ &= \alpha \left(\alpha + (1-\alpha)\left(\frac{l}{k}\right)^{\frac{\eta-1}{\eta}}\right)^{-1}. \end{aligned} \tag{25}$$

But as we have already derived, the capital-labor ratio depends only on r, w, τ_g^r, and τ_g^l; consequently, ϵ_k also depends only on r, w, τ_g^r, and τ_g^l. 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 similar result can be derived for ϵ_l.

B Main Data Source

B.I Survey Inclusion

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

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

2. The business was *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 proprietorship, 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 it made state unemployment insurance payments;

   (d) reported that 2004 was the first year it made federal insurance contribution act payments.

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

B.II Sample Selection

As discussed in the main text, our analysis focuses on contrasting the various outcomes between Black-owned and White-owned firms. To that end, we need to take a stand on what constitutes a "Black-" or "White-" owned firm. In this context, we classify a firm as "Black-owned" if the primary owner-operator is self-reported as Black, and a firm is classified as "White-owned" if the primary owner-operator is classified as "White". Note that the primary owner-operator is the survey respondent, and typically either the sole operator of the firm, or the majority shareholder if the firm has multiple owners-operators. In turn, we restrict our analysis to this subset of firms and drop other observations for which the race of the primary owner-operator is of a different group.

Note that in the KFS, we actually observe the race of every single owner-operator of the surveyed firm. For instance, in theory, a firm could have three owner-operators, where the primary owner-operator identifies as Black, but the other owner-operators identify as White. In this case, based on our classification, this firm would be classified as "Black-owned".

While potentially a concern, we found that such issues do not occur in practice. Importantly, approximately 71% of firms only have a single owner-operator, and 24% have two owner-operators, meaning that these two categories of firms make up virtually all our observations. For the former, this issue of "misclassification" would not arise. For the latter, we find that conditioned on being classified as a "Black-owned" firm, only 8% of firms report have a White owner-operator. Likewise, there are virtually no White-owned firms that reported having a Black business partner.

Finally, because our analysis relies on observing the revenue, non-cash assets, and employment of the firm, we only consider firms that report at least $1000 in non-cash assets in our analysis.

B.III Variable Construction

We describe here how we construct measures of the capital-labor ratio, and the average revenue products of capital and labor. Note that to avoid outliers from driving the analyses, we also always winsorize these three variables at the 5% level.

B.III.1 Capital

The KFS provides the balance sheet of the firm, and it provides a breakdown of the type of capital assets that the firm owns. However, as in most standard models, we consider only a single generic capital asset of interest. In order to 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:

$$K_{i,t} = \sum_j \frac{K_{i,j,t}}{P_{j,t}},$$

where $P_{j,t}$ is the relative price of each capital type j 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.

It is important here to note that the values of the capital stock reported in the KFS are technically "year-end" balance sheet variables. In other words, the value of capital reported in the survey year s is technically "utilized" in the year $s + 1$.

B.III.2 Revenue

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

B.III.3 Value added and ARPK

One of the key variable of interest is the average revenue product of capital of the firm, which is simply the ratio of revenue to capital. That said, note that while we use the term "revenue" following convention, the correct object of interest is "value added", since our production technology features only two factors of input (capital and labor, but no intermediates).

Unfortunately, the KFS does not provide measures of intermediate inputs for computing value added, nor does it provide direct measures of value added. Therefore, we follow the literature (e.g., David and Venkateswaran (2019)) by obtaining the material share at the 2-digit NAICS code level, and use the material share to back out the implied value added from observed total revenue. ARPK is then trivially the ratio of value added to capital.

B.III.4 Labor, Capital-Labor Ratio, and ARPL

Our final variables of interest are the capital intensity, proxied by the capital-labor ratio of the firm, and ARPL. As discussed in the main text, we compute labor as the sum total of employees and owner-operator of the firm. The capital-labor ratio is then simply the ratio of the capital stock to employment, while ARPL is simply the ratio of value added to labor.

C Additional Data Sources

C.I Federal Procurement Spending

The Federal Procurement Spending data are a collection of over 400 data elements coming from various government systems. These data elements cover information about federal agencies, agency accounts, award types (contracts, grants, and loans), prime award recipients, and sub-recipients, as well as information such as Census data for additional context from fiscal year 2001 to present (For more details, please see www.usaspending.gov). More importantly, the federal awards or contracts are available at the county level or congressional district level, with the names and zip codes of the recipients. To make the merge possible with the KFS data, we restrict the deaggregation at the county level since the KFS does not have the names of the firms due to confidentiality reasons.

Table A1 provides an overview of the distribution of the federal procurement spending at the county level, where we restrict our sample to counties having both total positive contracts and positive contracts for Black recipients. On average, the allocation of these federal contracts is right-skewed both for all firms and the subsample of Black recipients. This implies that for any given county, receiving a federal procurement is not frequent, but when a firm does receive it, the amount is quite substantial.

Table A1: Summary Statistics using the Federal Procurement Spending

	mean	std. dev.	p25	p50	p75	p95
All(millions of $)	9,120	66,700	12.20	104	1,030	24,300
Black(millions of $)	31.70	225	0.07	0.77	5.20	91.60
Black share of all(%)	11.06	24.56	0.08	0.71	5.75	85.03

Notes: This table provides summary statistics of the Federal Procurement Spending data. The statistics are computed using only a subsample of counties that report both positive procurement and positive procurement for Black businesses. Each observation is a count-year. Figures are rounded to two decimal places or the nearest whole number, where appropriate.

C.II Current Population Survey

We use an extract from the (monthly) IPUMS CPS harmonized microdata, which covers the year 1962 to the present. We focus on demographic information and income, for the years 2004 to 2011. Consequently, we compute at the county-year level, the population count of Black and White individuals, the share of Black individuals relative to total individuals, and the average income of Black and White households. These county-year variables are then merged back into the KFS to carry out the relevant analyses.

C.III Survey of Consumer Finances

We use the 2004 wave of the Survey of Consumer Finances (SCF) to construct racial wealth gaps for business owners and relate these estimates to the markup wedge discussed in the main text. We focus on the subsample of entrepreneurs defined as business owners(active/non-active) or self-epmployed.

Three main variables are then use to compute key descriptive statistics as displayed in the table A2, where the last panel shows the White-Black wealth ratio. Business net market value is the net equity if business was sold today, while business market value is just the revenue to be received once the business is sold without paying its debt. Net worth is the difference between assets and debt of the household. The main text references the White-Black ratio for next market value.

Table A2: Summary Statistics for business owners in the SCF 2004

	White				
	mean	p25	p50	p75	p95
Bus. net market value	589,463	0	38,000	250,000	2,206,000
Bus. market value	152,787	0	8,800	50,000	550,000
Networth	1,591,404	141,800	462,900	1,079,720	6,739,800
	Black				
	mean	p25	p50	p75	p95
Bus. Net market value	208,248	0	500	70,000	542,000
Bus. market value	37,833	0	50	17,000	160,000
Net worth	406,288	9,500	38,820	233,500	750,200
	W-B ratio				
Bus net market value	2.83	-	76.00	3.57	4.07
Bus. market value	4.04	-	176.00	2.94	3.44
Net worth	3.92	14.93	11.92	4.62	8.98

C.IV Details of the SSBF

The SSBF was designed to provide cross-sectional information about a nationally representative sample of small businesses in the United States, and was conducted by the Federal Reserve in three separate waves (1994, 1999, and 2004; in turn, these waves survey firms regarding business conditions for the years 1993, 1998, and 2003). In general, the survey included only firms with less than 500 employees, and represent a random sample of small business firms that are stratified by size, geographic location, race, and gender. The SSBF contains similar information to the KFS; however, unlike the KFS which is designed to be representative of all *startups* in the year 2004, the SSBF is designed to be representative of all small businesses for their respective survey years.

Because the variables in the SSBF are not always exactly the same as those of the KFS, it is useful to provide context as to the relevant associated variables we use from the SSBF. In the case of our dependent variables, these variables are closely aligned with that of the KFS. For instance, the capital stock is characterized by the net book value of any buildings and equipment or any other depreciable, depletable or intangible assets augmented with the net book value of land inventory merchandise and production materials; likewise, labor is defined as the sum total of employees and the number of owners working in the firm. For control variables, we utilize education, age, years of experience, percentage of ownership, gender, and wealth (except for the 1993 wave, where information of wealth is not available). Unlike the KFS, wealth is a continuous variable, measured as the net worth of the individual, which we include in our regression specification in logs. For wages, we also compute an imputed wage rate as in the KFS.

We note a few key differences between the KFS and each wave of the SSBF for the construction of the labor and imputed wage variables. For the 2003 wave of the SSBF, total labor compensation is broken down into workers' and officers' compensation. Given the greater granularity in compensation, we utilize the officers' compensation component to impute the owners' wages. For the 1998 wave, we do not observe labor compensation. As such, we replace labor compensation with total cost as a control variable. Finally, for the 1993 wave, we observed unexplained irregularities with the variable that defines the number of owners. As such, we code labor as simply "full-time equivalent" employees, and only use the set of firms that are employers.

D Additional Figures, and Tables

D.I Additional Figures

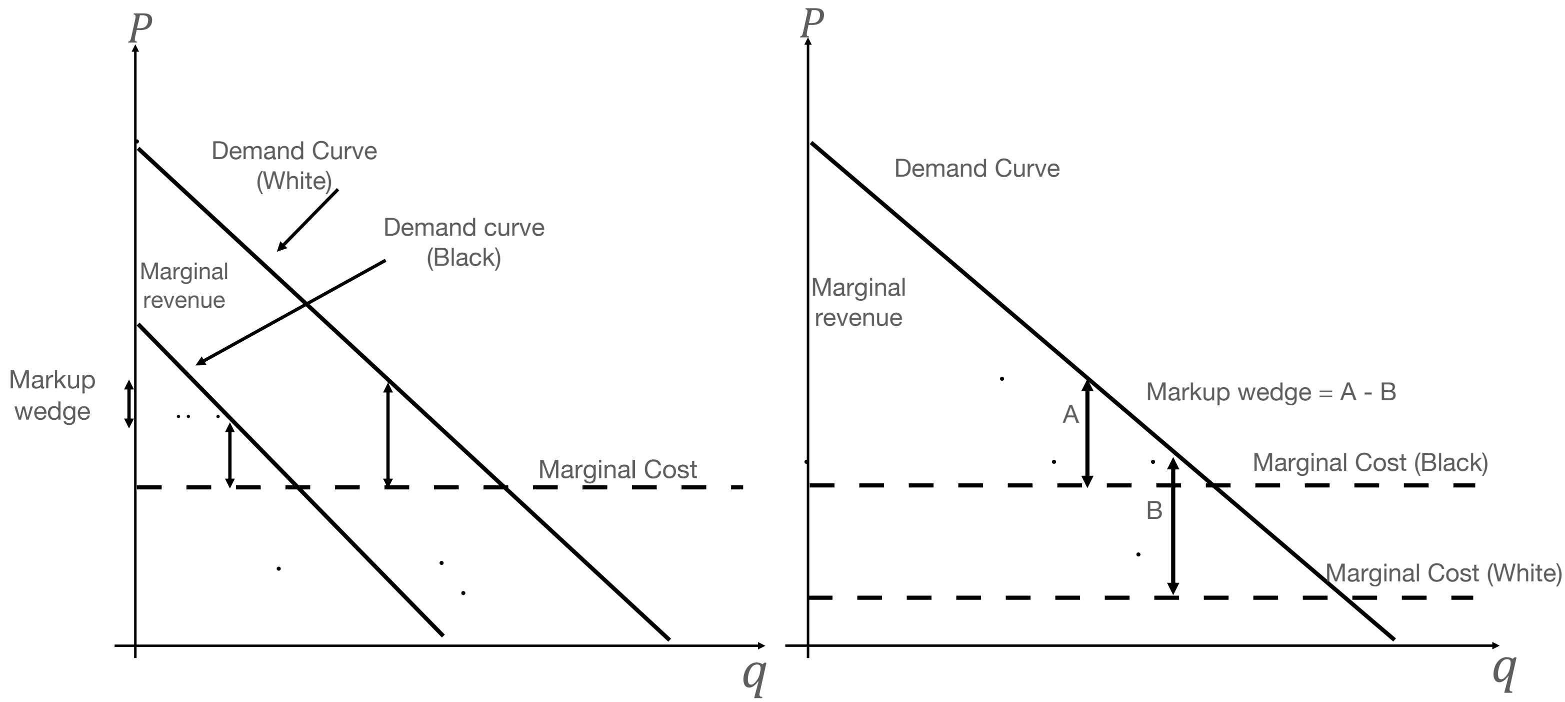
D.I.1 Graphical summary on identification of demand differences

In the left panel of Figure A1, we illustrate our identification argument, building in the assumption that physical productivity across groups is identical. As we can see, higher demand generates higher markups via higher prices, but marginal cost curves are identical by assumption.

In the right panel of Figure A1, we now plot the effect of physical productivity differences, assuming identical demand (i.e., no consumer discrimination). In this context, as we discussed in the main text, higher physical productivity firms charge a higher markup but also simultaneously charge lower prices due to lower marginal costs.

Figure A1: Identifying demand differences

The figures illustrate markup difference due to differences in demand (left) and differences in productivity (right), per the discussion in the main text.



D.II Additional Tables

D.II.1 Estimates for the Labor Wedge

We report below our estimates of the labor wedge. While not a focus of our paper, we note that we uncover a *negative* labor wedge; in other words, we find that Black-owned firms implicitly receive a labor subsidy. Importantly, this implies that if we had naively estimated Equation 6 with a race indicator variable, and interpreted that as the capital wedge, we would have over-estimated the true capital wedge.

Table A3: Baseline Estimates of the Labor Wedge

	(1)	(2)	(3)	(4)
δ^l	-0.171	-0.136	-0.046	-0.118
	(0.075)	(0.065)	(0.086)	(0.091)
Observations	8832	8553	4399	4399
R^2	0.135	0.162	0.208	0.161
Controls	No	X	X, wealth	X, 2008+

Notes: This table reports our estimates for the labor wedge. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

D.II.2 SSBF Results

We report below our estimtaes of the markup and capital wedge using the SSBF.

Table A4: Baseline Estimates of the Markup and Capital Wedges in the SSBF: 2003 wave

	(1)	(2)	(3)
	Panel A: Markup Wedge		
δ^{μ}	-1.041	-0.908	-0.882
	(0.091)	(0.089)	(0.088)
Observations	3,215	3,209	3,209
R^2	0.548	0.580	0.586
	Panel B: Capital Wedge		
δ^{r}	0.302	0.195	0.169
	(0.146)	(0.145)	(0.145)
Observations	3,215	3,209	3,209
R^2	0.020	0.039	0.039
Controls	No	X	X, wealth

Notes: This table reports our estimates for the markup and capital wedges. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Table A5: Baseline Estimates of the Markup and Capital Wedges in the SSBF: 1998 wave

	(1)	(2)	(3)
	Panel A: Markup Wedge		
δ^{μ}	-0.602	-0.469	-0.454
	(0.092)	(0.091)	(0.091)
Observations	2,724	2,609	2,609
R^2	0.540	0.569	0.573
	Panel B: Capital Wedge		
δ^{r}	0.242	0.230	0.212
	(0.390)	(0.140)	(0.140)
Observations	2,724	2,609	2,609
R^2	0.022	0.050	0.050
Controls	No	X	X, wealth

Notes: This table reports our estimates for the markup and capital wedges. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Table A6: Baseline Estimates of the Markup and Capital Wedges in the SSBF: 1993 wave

	(1)	(2)	(3)
	Panel A: Markup Wedge		
δ^{μ}	-0.141	-0.139	–
	(0.069)	(0.069)	–
Observations	3,328	3,317	–
R^2	0.669	0.673	–
	Panel B: Capital Wedge		
δ^{r}	0.084	0.063	–
	(0.124)	(0.124)	–
Observations	3,328	3,317	–
R^2	0.025	0.033	–
Controls	No	X	X, wealth

Notes: This table reports our estimates for the markup and capital wedges. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

E Additional Analyses

E.I Statistical Decomposition of the Markup and Capital Cost Wedge

Our estimation framework fundamentally leverages on "unexplained differences" in capital returns and capital intensity across Black- and White-owned firms to identify the markup and capital wedge. However, it is clear from our analysis that a substantial variation of both capital returns and intensity can be explained due to simply different observable factors (e.g., wealth and risk). Therefore, to refine our analysis, we present a statistical decomposition of the difference in capital returns and capital intensity. This allows us to understand the fraction of variations in capital returns and capital intensity that are actually due to race, relative to the variation that can be explained by observable factors.

To that end, we follow a long tradition in the labor economics literature by utilizing the decomposition technique of Oaxaca (1973) and Blinder (1973). In particular, we use a so-called "pooled" estimator, that decomposes the average difference in an outcome into an "explained" component (a component that can be statistically explained by observables), and an "unexplained" component (residual difference that cannot be explained by observables; in our case, this would be the coefficient on the race indicator variable in our regression specification).[21] For our explanatory variables, we use our baseline set of controls.

Table A7 reports all our results. In summary, the top panel reports the "difference", "explained", and "unexplained" components coming from the decomposition. "Difference" here refers to the average difference in the outcome variable, while "explained" and "unexplained" are as described above. In the bottom panel, we report the differences that are "explained" by the top two most important covariates in terms of "explaining" the differences in capital returns and capital intensity.

[21] The implementation is done using Stata's oaxaca command, and incorporating the survey weights provided by the KFS.

Table A7: Decomposition of capital returns and capital intensity

	(1) ARPK		(2) Capital-Labor Ratio	
Total Difference	-0.316 (0.096)		-0.549 (0.085)	
Explained	0.391 (0.068)		-0.167 (0.036)	
Unexplained	-0.707 (0.062)		-0.382 (0.084)	
Top 2 covariates	$\log \frac{k}{l}$	0.366 (0.059)	Wages	-0.0734 (0.016)
	Hours worked	0.0757 (0.027)	Hours worked	0.0230 (0.009)

Notes: Oaxaca/Blinder decomposition of differences in capital returns and capital intensity. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Column 1 reports the decomposition for capital returns, using the same sample for analysis as in Table 2. Here, we find a striking result: The explained component of capital returns is *positive* (0.391 log points), that is, based on the observables alone, we would have concluded that Black-owned firms should operate with higher returns. Looking to the second panel, we see the reason: Capital-intensity alone implies a 0.366 log point higher returns, capturing about 94% of the explained differences. In other words, much of the increases in returns is not due to higher markups; rather, it is simply due to the capital constraints we identified (i.e., higher implicit cost of capital). Indeed, this finding, that financially constrained firms have higher ARPK, would be the typical result one would find (e.g., Morazzoni and Sy (2022); Bento and Hwang (2022a); Goraya (2023)) if we abstracted away from endogenous markups.

Next, we observe that the remaining variation in the explained component is essentially absorbed by hours worked. Indeed, in the KFS, we find that the average Black owner works about 2 hours more than a White owner, which in turn translates into 0.0757 log points higher returns. That said, it is important to keep in mind that this is not causal, that is, returns are not higher simply because Black owners work longer hours.

Next, in Column 2, we report a similar decomposition exercise for capital intensity, again using the same sample for analysis as in Table 2. Here, we see that about 30% of the differences can be explained by our covariates. Notably, we find that differences in wages between Black- and White-owned firms explain the bulk of the "explained" component (about 44%). In other words, Black-owned firms operate with lower capital intensity because they face lower labor costs.

In the main text, we also found that risk and wealth appears to explain a bulk of the capital wedge. Therefore, we now further explore the role of risk and wealth in driving the differences in capital intensity. To begin, we first re-estimate the statistical decomposition exericse using the subsample of firms for which we observe the three measures of risk (FSSP, Paydex, and Credit Scores) available to us from the KFS, as well as firms for which we observe wealth. Our results are reported in Column 1 of Table A8. Similar to the full sample, we find that about 50% of the differences can be explained by our control variables, although the total difference in capital intensity is smaller for this subsample.

Table A8: Decomposition of capital intensity: The role of risk and wealth

	(1)	(2)	(3)
Total Difference	-0.298 (0.153)	-0.298 (0.154)	-0.298 (0.154)
Explained	-0.148 (0.075)	-0.190 (0.082)	-0.264 (0.089)
Unexplained	-0.150 (0.149)	-0.108 (0.151)	-0.034 (0.145)
Controls	Baseline	With Risk	With Risk and Wealth

Notes: Oaxaca/Blinder decomposition of differences in capital intensity. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

Next, in Column 2, we additionally include the three measures of risk as a control variable. We find that the total explained component rises to about 64%, suggesting a large role for risk. However, risk alone does not subsume all the differences. Finally, in Column 3, we control for wealth, in addition to risk. Here, we see that wealth has a huge statistical importance, where the total explained component rises to almost 89%.

It is illuminating to review our results in comparison to Fairlie et al. (2020), who also conduct a statistical decomposition using the KFS aimed at uncovering the degree to which a "racial gap in funding" is associated with observable differences (i.e., risk, wealth, and so on). Using differences in firm sizes alone, the authors conclude that about half of the gap in funding is attributed to race alone, after controling for observable differences. This led the authors to conclude that a large fraction of the gap in firm sizes is due to the "attitudes and perceptions by and about black borrowers in credit markets". In contrast, using a similar set of control variables, we find that the unexplained component is virtually negated; in other words, differential capital supply does not appear to be the driver of why Black-owned firms are smaller relative to White-owned firms.

E.II Test of Classification of Homogeneous Goods Sector

As a placebo test of our identification strategy and classification choice, we estimate Equation 16 but simply 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. Thus, if our strategy is valid, we should detect no differences for Black individuals operating in industries with relatively greater homogeneity of output. Indeed, as we report in Table A9, in all specifications considered, Black individuals running businesses in industries with relatively more homogeneous outputs do not operate with capital intensities that are different from those of firms operating in industries with less homogeneous outputs.

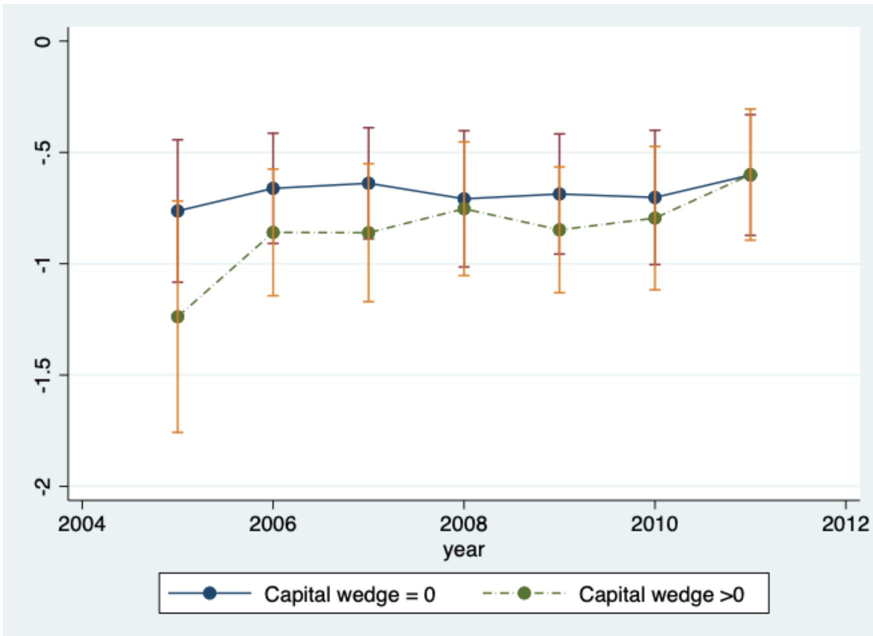
Table A9: Test of homogeneous goods sector assumption

	(1)	(2)	(3)	(4)
δ	-0.307	-0.367	-0.147	-0.304
	(0.100)	(0.102)	(0.129)	(0.132)
ν	0.240	0.332	0.174	0.276
	(0.241)	(0.244)	(0.279)	(0.279)
Controls	No	X	X, wealth	X, 2008+
Observations	6730	6504	3299	3299
R^2	0.119	0.162	0.200	0.157

Notes: This table reports our estimation results per Equation 16 but using the log capital-labor ratio as a dependent variable. The estimates of interest are δ and ν. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are in parentheses and are robust standard errors that accounting for sampling weights. All figures are rounded to 3 decimal places.

E.III Markup Wedge and Initial Conditions in Financing

Figure A2: Markup wedge over time for firms split by initial conditions.



Markup wedge over time for Black-owned and White-owned firms, split by initial conditions.

E.IV Addressing Survivorship Bias

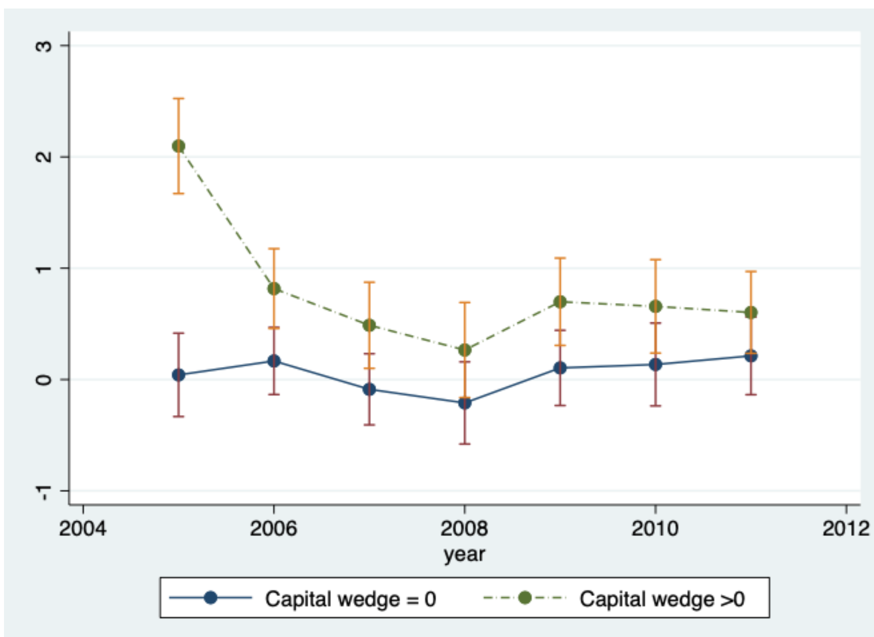
While we argue that the reduction in the capital cost wedge is driven by self-accumulation of assets, a threat to our argument is the possibility of survivorship bias. Specifically, there is a possibility that there is a specific capital intensity threshold for survival. Since we rely on variations in capital intensity to identify the capital wedge, this would mechanically bias us towards finding a reduction in the capital wedge without Black entrepreneurs engaging in a higher savings rate.

To address this concern, we use the subsets of White-owned firms described in Section 5.3, and now estimate the capital cost wedge year-by-year for each subset. The results are presented in Figure A3 below.

As a start, we first observe the dynamics of the capital wedge for the subset of White-owned firms that had no capital wedge relative to Black-owned firms (blue lines). As we can see, through out the entire sample, the wedge stays effectively zero (and is never statistically different from zero). 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)).

Next, we observe from the green line that the decrease in capital wedge we presented in the main text is essentially driven by a closing of the gap between the high capital-intensity firms and the lower capital-intensity firms.

Figure A3: Capital wedge over time for Black-owned and White-owned firms, split by initial conditions.



Capital wedge over time for Black-owned and White-owned firms, split by initial conditions

E.V Robustness Checks on Definition of Labor

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.

E.V.1 Full-Time Workers Only

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

Table A10: Estimates of the Markup and Capital Wedge: Full-Time Workers Only

	(1)	(2)	(3)	(4)
		Panel A: Markup Wedge		
δ^{μ}	-0.574	-0.634	-0.480	-0.602
	(0.081)	(0.078)	(0.103)	(0.106)
Observations	5202	5010	2492	2492
R^2	0.480	0.505	0.569	0.538
		Panel B: Capital Wedge		
δ^{r}	0.144	0.207	0.069	0.159
	(0.120)	(0.114)	(0.151)	(0.152)
Observations	5202	5010	2492	2492
R^2	0.148	0.170	0.195	0.149
Controls	No	X	X, wealth	X, 2008+

Notes: This table reports our estimates for the markup and capital wedges where part-time workers are excluded in the measure of labor. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

E.V.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 A11: Estimates of the Markup and Capital Wedge: Employer Firms Only

	(1)	(2)	(3)	(4)
		Panel A: Markup Wedge		
δ^{μ}	-0.575	-0.626	-0.472	-0.600
	(0.080)	(0.077)	(0.103)	(0.106)
Observations	5208	5015	2495	2495
R^2	0.508	0.529	0.596	0.563
		Panel B: Capital Wedge		
δ^{r}	0.131	0.186	0.058	0.157
	(0.113)	(0.108)	(0.151)	(0.152)
Observations	5208	5015	2495	2495
R^2	0.172	0.194	0.233	0.189
Controls	No	X	X, wealth	X, 2008+

Notes: This table reports our estimates for the markup and capital wedges for the subsample of employer firms. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.

E.V.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 A12: Estimates of the Markup and Capital Wedge: Employer Firms and Full-Time Workers Only

	(1)	(2)	(3)	(4)
	Panel A: Markup Wedge			
δ^{μ}	-0.574	-0.634	-0.480	-0.602
	(0.081)	(0.078)	(0.103)	(0.106)
Observations	5202	5010	2492	2492
R^2	0.480	0.505	0.569	0.538
	Panel B: Capital Wedge			
δ^{r}	0.109	0.161	0.050	0.147
	(0.114)	(0.108)	(0.151)	(0.152)
Observations	5202	5010	2492	2492
R^2	0.148	0.170	0.195	0.149
Controls	No	X	X, wealth	X, 2008+

Notes: This table reports our estimates for the markup and capital wedges for the subsample of employer firms, and where we exclude part-time workers in the measure of labor. All other coefficients are suppressed for the sake of brevity. Each column reports the result associated with a set of control variables or sample subset as described in the main text. All regressions include year and 2-digit industry fixed effects. Standard errors are robust standard errors accounting for sample weights, and shown in parentheses. All figures are rounded to 3 decimal places.